Problem Statement:

Dataset: Polish companies bankruptcy data

https://archive.ics.uci.edu/ml/datasets/Polish+companies+bankruptcy+data

This dataset is about the bankruptcy prediction of Polish companies.

This dataset basically contains the financial data for companies for a particular year in the study period and labels if a company went bankrupt after some years. There are five subsets of the whole dataset based on the year of study chosen. Selected is the subset in which the financial data available is of 2nd year of the study period, and bankruptcy status is after 4 years. This data has 10173 instances, 64 attributes, and 1 label column stating if the company went bankrupt or not.

Proposal: This data will be split into Training Set and Test Set.

Train two different machine learning models on the training set.

With machine learning models, we will try to predict the bankruptcy status on the test set,

and compare the performance of the model on various metrics such as Precision, Accuracy, Recall, F1 score, etc

This problem makes business sense in the fact that this approach could be used by financial institutions to predict the future financial status of the companies before approving their loans.

Cleaning: This dataset has missing values. So, we will be selecting the appropriate method to fill up these missing values. One of the options could be to replace missing values with the average of the entire column. Also, if one or two attributes have too many missing values, we will be removing those attributes from the dataset.

Additionally, from EDA, if we find that an attribute does not have much variation along the entire dataset, then it means that this attribute has poor information content, so we might ignore that attribute as well.

Finally, since 64 features are relatively high for a machine learning model to perform well, so we will be using the Principal Component Analysis (PCA) approach to reduce the dimensionality of this dataset.

For the machine learning models, We propose to use Gaussian Mixture Models for one of the models, and Random Forest for the other model

In [ ]:
```
# Importing the Dataset from GitHub where it was uploaded
link='https://raw.githubusercontent.com/sran-gurkaran/Auto_ML_on_Azure/main/Year_2_Bankruptcy_Data.csv'
import pandas as pd
import numpy as np
df=pd.read_csv(link,encoding='unicode_escape')
```

```
/anaconda/envs/azureml_py38/lib/python3.8/site-packages/IPython/core/interactiveshell.py:3139: DtypeWarning: Columns (0,1,2,5,6,8,9,10,13,17,21,23,24,28,34,35,37,47,50,54,56,58) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

In [ ]:
```
# Printing the Dataset
df
```

Out[ ]:

	net profit / total assets	total liabilities / total assets	working capital / total assets	current assets / short-term liabilities	[(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365	retained earnings / total assets	EBIT / total assets	book value of equity / total liabilities	sales / total assets
0	0.20235	0.465	0.24038	1.5171	-14.547	0.51069	0.25366	0.91816	1.1519
1	0.030073	0.59563	0.18668	1.3382	-37.859	-0.00031864	0.04167	0.6789	0.32356
2	0.25786	0.29949	0.66519	3.2211	71.799	0	0.31877	2.332	1.6762
3	0.22716	0.6785	0.042784	1.0828	-88.212	0	0.28505	0.47384	1.3241
4	0.085443	0.38039	0.35923	1.9444	21.731	0.1879	0.10823	1.3714	1.1126
...	...	...	...	...	...	...	...	...	...
10168	0.02997	0.66806	0.066243	1.1103	-105.55	0.02997	0.038888	0.48274	1.0292
10169	0.012843	0.49306	-0.16062	0.61898	-24.801	0.012843	0.012843	0.9059	1.0145
10170	0.015092	0.55759	-0.2846	0.48599	-85.571	0.015092	0.0098258	0.69488	1.006
10171	-0.0025542	0.47076	0.42401	1.9007	0.95483	-0.0025542	0.0017845	1.1144	0.99293
10172	0.0020717	0.94315	-0.13474	0.85607	-119.92	0.015226	0.0020717	0.059818	1.7749

10173 rows × 65 columns

In [ ]:
```
# Shuffling the Dataset as the Bankrupt Companies are collected all together at end of the dataset
np.random.seed(10)
df_shuffled=pd.DataFrame(np.random.permutation(df),columns=df.columns)
df_shuffled.tail(5)
```

Out[ ]:

	net profit / total assets	total liabilities / total assets	working capital / total assets	current assets / short-term liabilities	[(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365	retained earnings / total assets	EBIT / total assets	book value of equity / total liabilities	sales / total assets	equity tot asset
10168	0.031424	0.64435	0.017886	1.0516	2.5855	0	0.064682	0.55196	1.2113	0.3556
10169	0.14743	0.11623	0.12241	2.0569	1155.7	0	0.14743	7.6036	2.0764	0.8837
10170	-0.5367	0.078497	0.26824	5.9054	48.959	0	-0.5367	11.739	0.80237	0.921
10171	0.46735	0.39807	0.014838	1.0641	-7.4599	0.83668	0.46735	1.5121	1.3241	0.6019
10172	0.08304	0.54857	0.24094	1.5541	-7.1571	0.23735	0.10727	0.65787	1.0909	0.3608

5 rows × 65 columns

This dataset is about the bankruptcy prediction of Polish companies.

This dataset basically contains the financial data of companies for a particular year in the study period and labels if a company went bankrupt after 4 years.
This data has 10173 instances, 64 attributes, and 1 label column stating if the company went bankrupt or not.

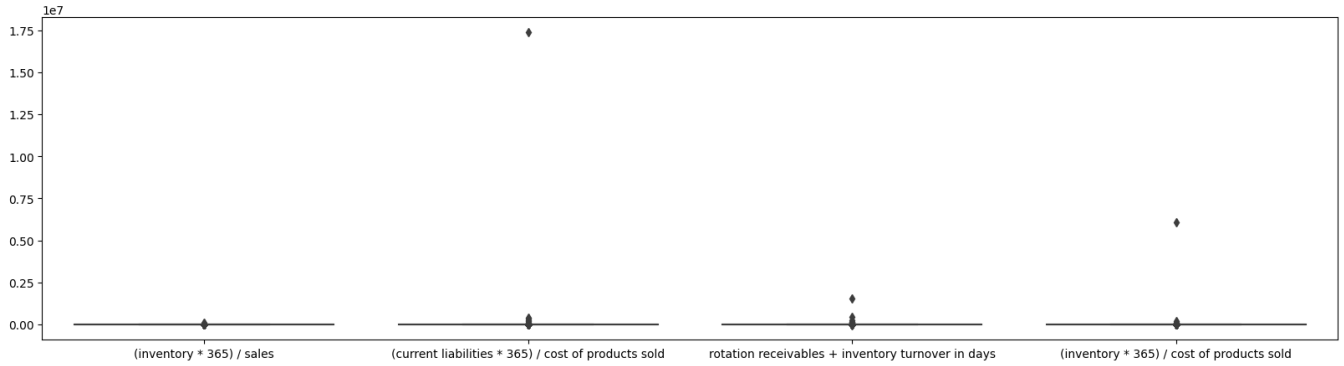
Exploring the Dataset :

In [ ]:
```
# Before We can start making even basic plots, we need to replace missing value
s '?' by NaN
DF=df_shuffled.copy(deep=False)
DF=DF.replace("?",'NaN')

# Now converting all values in the dataset to float values
DF=DF.astype(float)
```

In [ ]:
```
import seaborn as sns
from matplotlib import pyplot as plt
```

First, we will make some box plots to observe how our data is spread, and what is the extent to which outliers are present

In [ ]:
```
plt.figure(figsize=(20,5))
a1=DF.loc[:,[DF.columns[19]]]
a2=DF.loc[:,[DF.columns[31]]]
a3=DF.loc[:,[DF.columns[42]]]
a4=DF.loc[:,[DF.columns[46]]]
d=np.c_[a1,a2,a3,a4]

data_plot=pd.DataFrame(data=d,columns=[DF.columns[19],DF.columns[31],DF.columns
[42],DF.columns[46]])
P=sns.boxplot(data=data_plot)
```

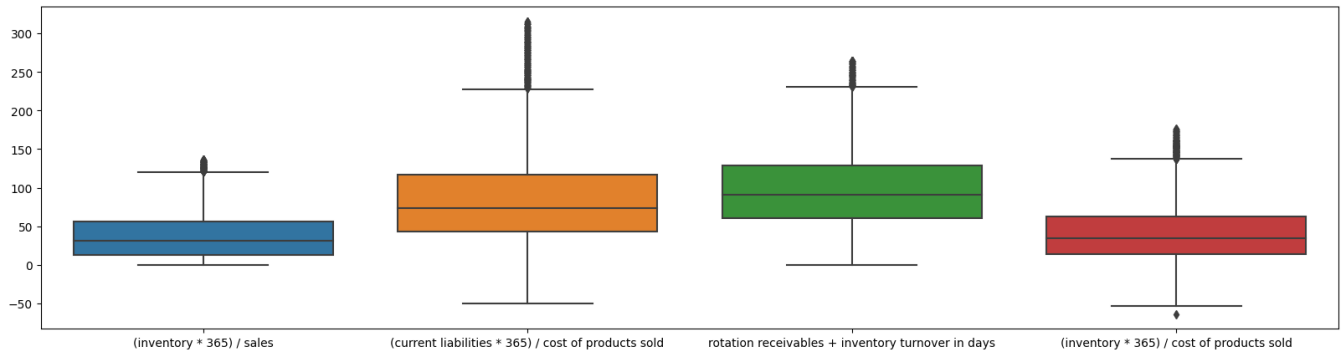


From above box plots, we see that there are outliers in data that will make further plotting difficult.
So, for only plotting purpose, we will make a function, which takes an array and returns another array in which the data points out of 6-sigma variation would not be present

In [ ]:
```
def filter (B):
   """This function excludes those values from an array which are outside the 6
-sigma variation"""
   A=B.copy()
   for k in range(0,5):
      l=np.nanmean(A)-3*np.nanstd(A)
      u=np.nanmean(A)+3*np.nanstd(A)
      na=float('NaN')
      Idx=(A<l)
      A[Idx]=na
      Idx=(A>u)
      A[Idx]=na
   return A
```

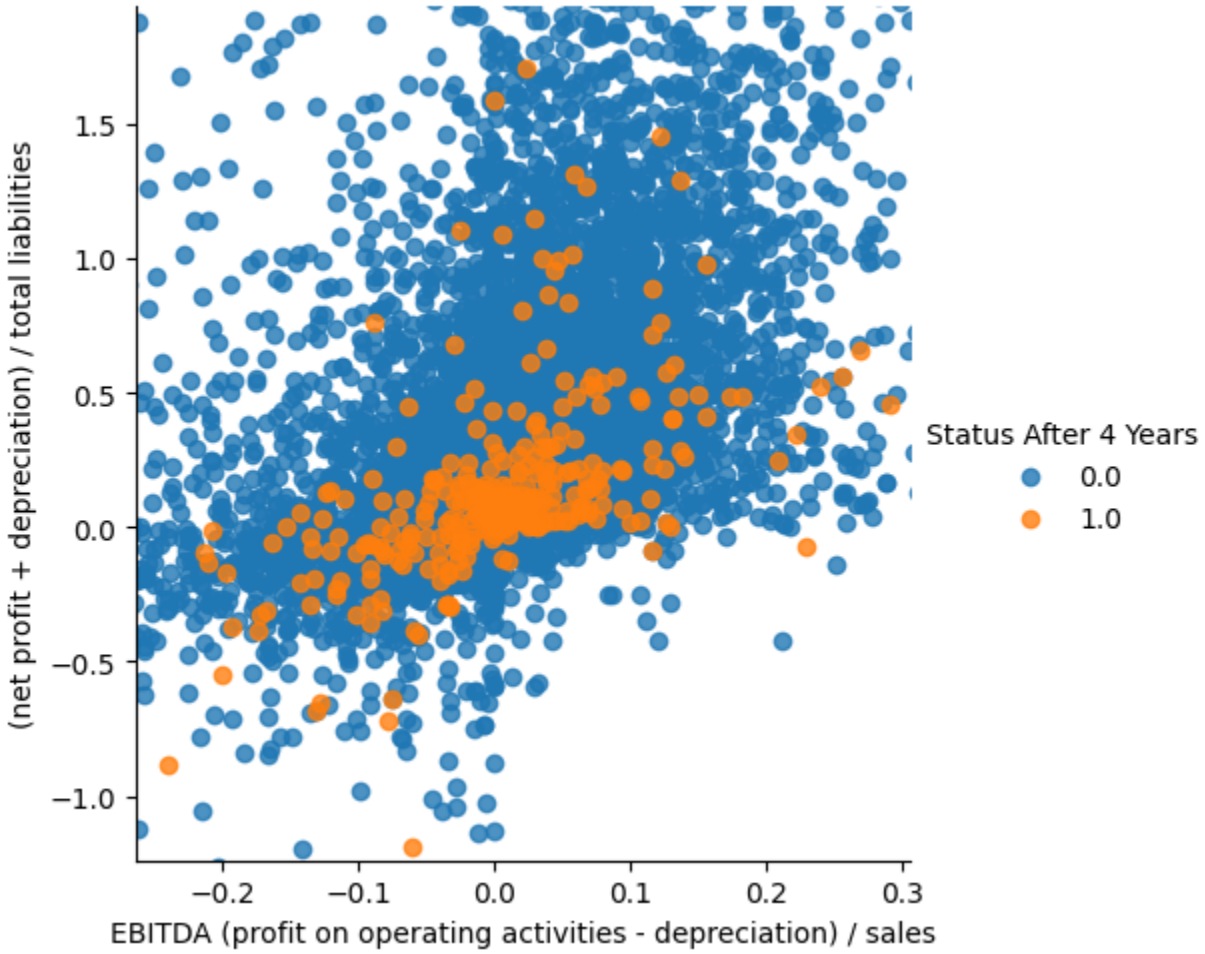
Now, we will again make the same box plots, but with data points removed which were out of 6-sigma variation

In [ ]:
```
plt.figure(figsize=(20,5))
a1=filter(DF.loc[:,[DF.columns[19]]])
a2=filter(DF.loc[:,[DF.columns[31]]])
a3=filter(DF.loc[:,[DF.columns[42]]])
a4=filter(DF.loc[:,[DF.columns[46]]])
d=np.c_[a1,a2,a3,a4]

data_plot=pd.DataFrame(data=d,columns=[DF.columns[19],DF.columns[31],DF.columns
[42],DF.columns[46]])
P=sns.boxplot(data=data_plot)
```



From above box plots, we see that our function did a good job in flitering the points which were out of 6-sigma variation. So, for further plotting, we will be using this function

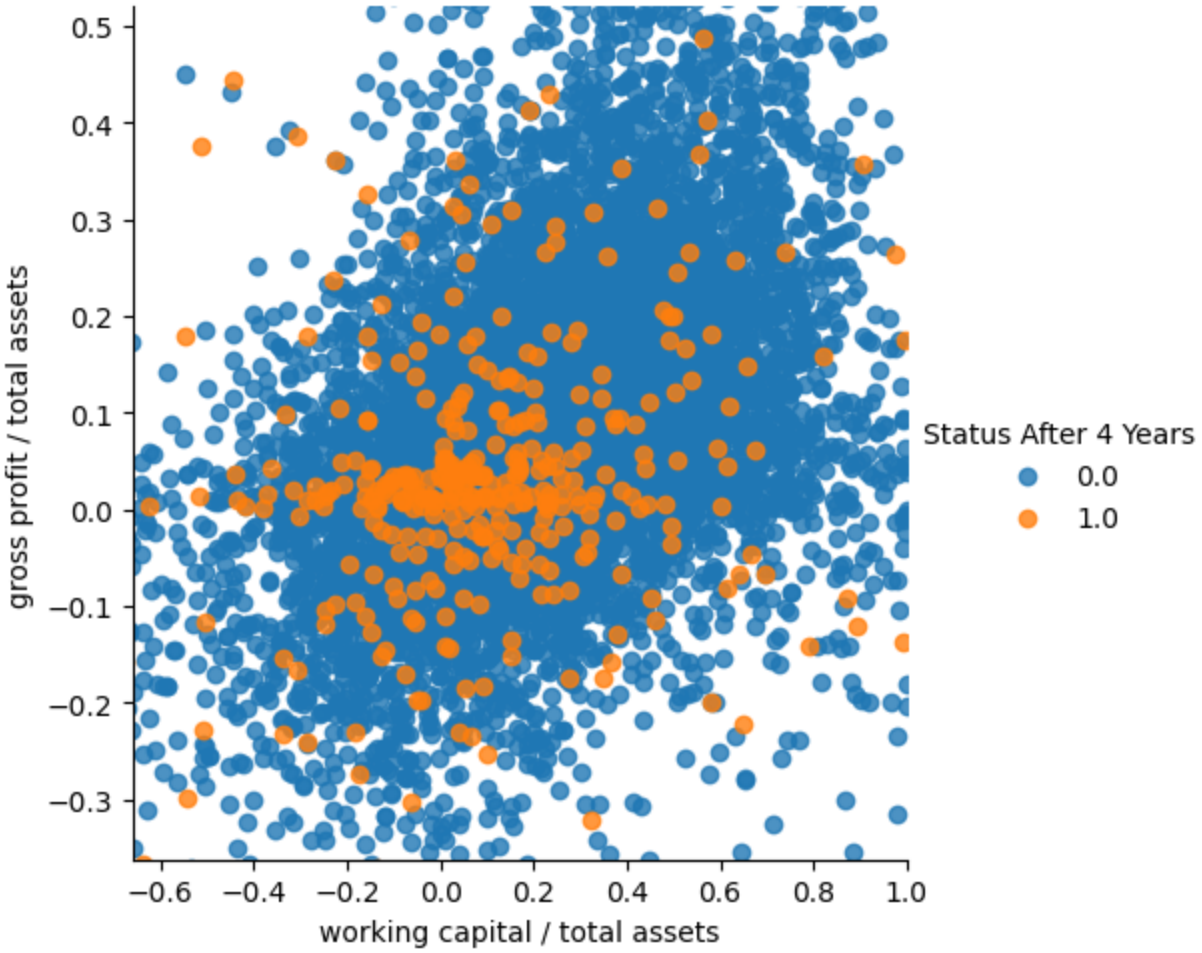
In [ ]:
```
# Firstly, We will try Scatter Plots between different combinations of attribut
e to observe if we can get some information out of them

# Scatter Plot -1
data_plot=DF.loc[:,[DF.columns[48],DF.columns[25],'Status After 4 Years']]
P=sns.lmplot(x=DF.columns[48],y=DF.columns[25],hue='Status After 4 Years',data=
data_plot,fit_reg=False)
x1=np.nanmin(filter(data_plot.iloc[:,0]))
x2=np.nanmax(filter(data_plot.iloc[:,0]))
y1=np.nanmin(filter(data_plot.iloc[:,1]))
y2=np.nanmax(filter(data_plot.iloc[:,1]))
P.set(xlim=(x1,x2))
P.set(ylim=(y1,y2));
```



The above plot shows that there is relevant information content in the attribute - '(net profit + depreciation) / total liabilities' as the data points with Status 1 are largely concentrated around zero.

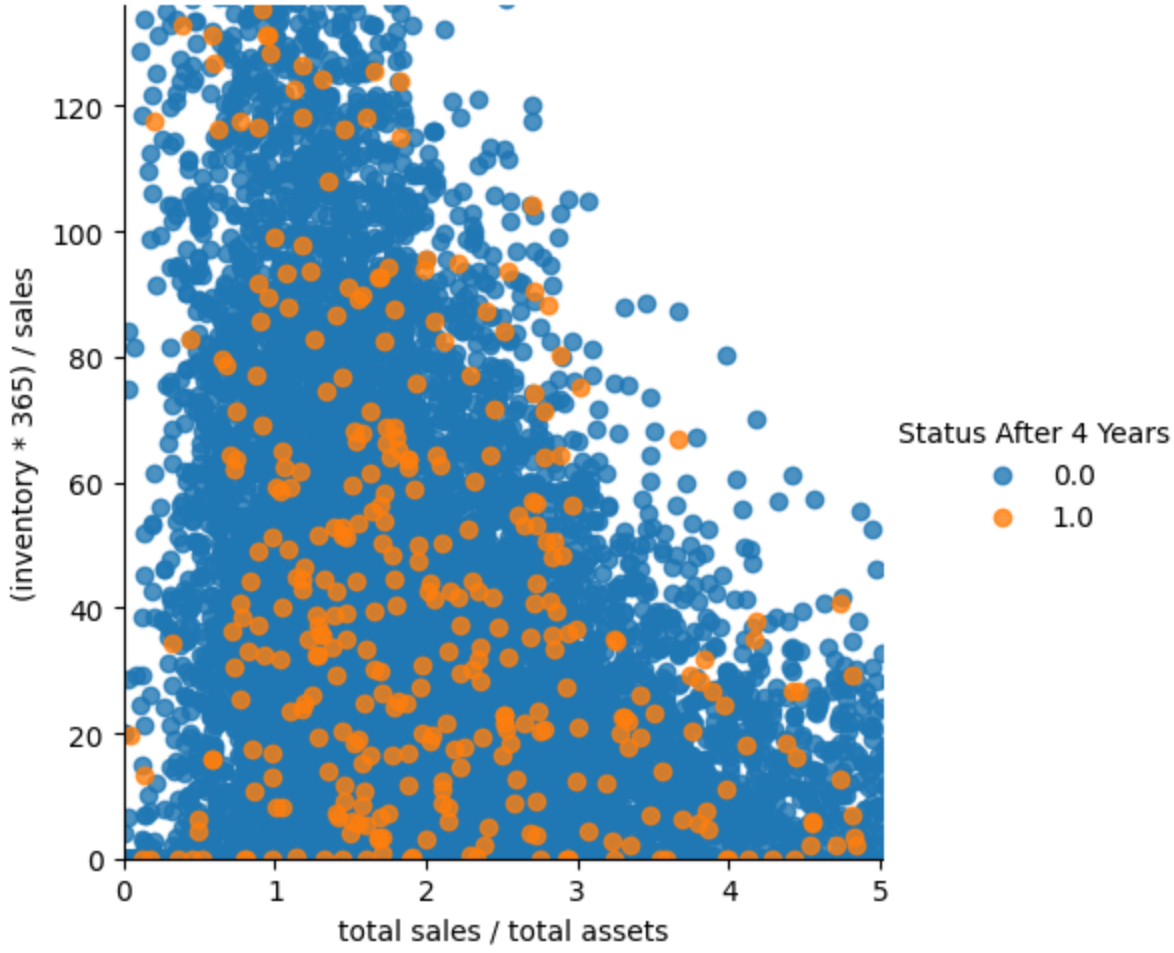
This plot also shows that the attribute - 'EBITDA (profit on operating activities - depreciation) / sales' , does not have significant variation between status 0 and 1.

In [ ]:
```
# Scatter Plot -2
data_plot=DF.loc[:,[DF.columns[2],DF.columns[17],'Status After 4 Years']]
P=sns.lmplot(x=DF.columns[2],y=DF.columns[17],hue='Status After 4 Years',data=d
ata_plot,fit_reg=False)
x1=np.nanmin(filter(data_plot.iloc[:,0]))
x2=np.nanmax(filter(data_plot.iloc[:,0]))
y1=np.nanmin(filter(data_plot.iloc[:,1]))
y2=np.nanmax(filter(data_plot.iloc[:,1]))
P.set(xlim=(x1,x2))
P.set(ylim=(y1,y2));
```



The above plot gives us an indication that both of theses attributes:
'working capital/total assets' and 'goss profit/total assets' are not best predictors for our objective.

In [ ]:
```
# Scatter Plot -3
data_plot=DF.loc[:,[DF.columns[35],DF.columns[19],'Status After 4 Years']]
P=sns.lmplot(x=DF.columns[35],y=DF.columns[19],hue='Status After 4 Years',data=
data_plot,fit_reg=False)
x1=np.nanmin(filter(data_plot.iloc[:,0]))
x2=np.nanmax(filter(data_plot.iloc[:,0]))
y1=np.nanmin(filter(data_plot.iloc[:,1]))
y2=np.nanmax(filter(data_plot.iloc[:,1]))
P.set(xlim=(x1,x2))
P.set(ylim=(y1,y2));
```



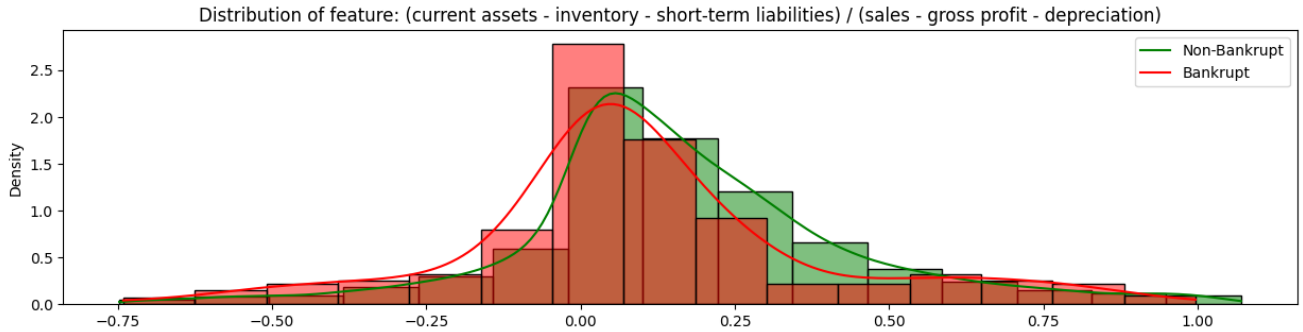
From above plot, we can see that both of the above attributes are not the ideal candidates for our predictors

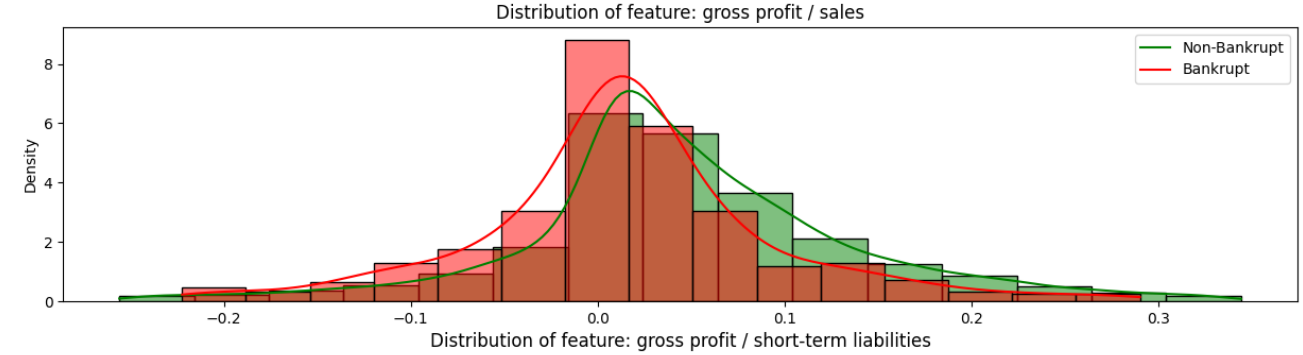
Now that we have made some scatter plots, we can say that although they give us an idea but not the whole picture, simply, because we cannot get information about the density of the datapoints

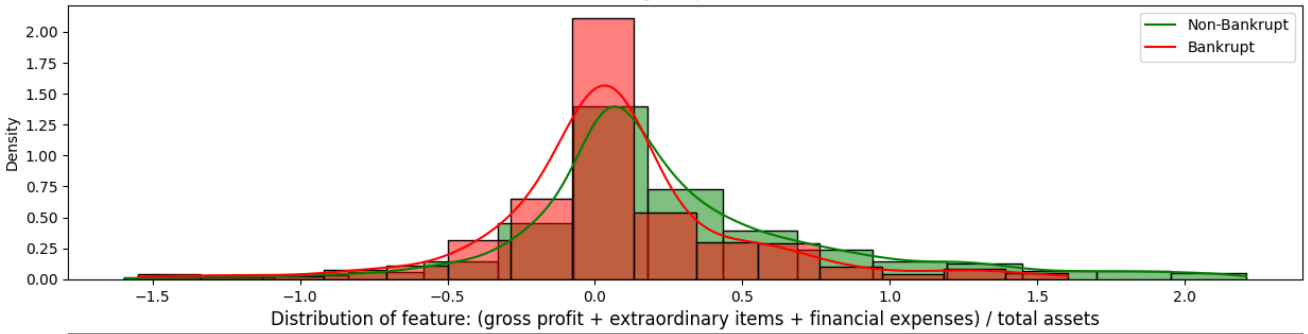
Therefore, we will try Distribution Plots

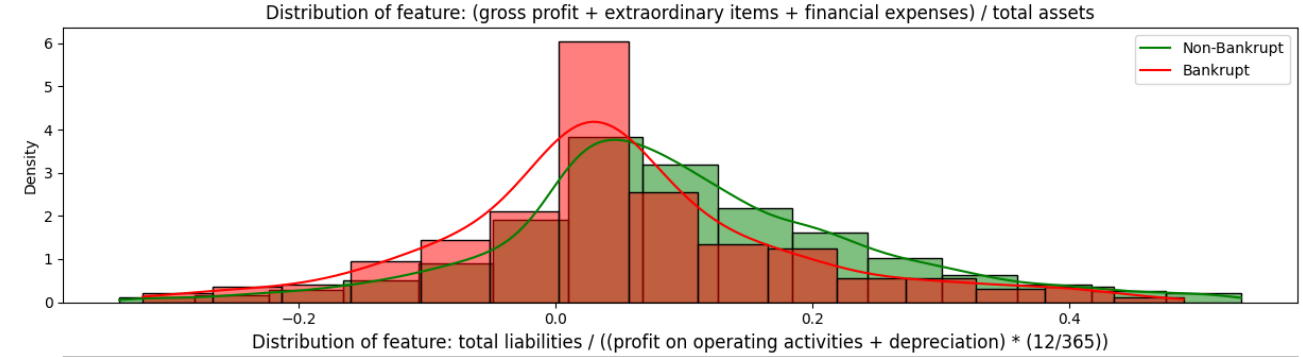
In [ ]:

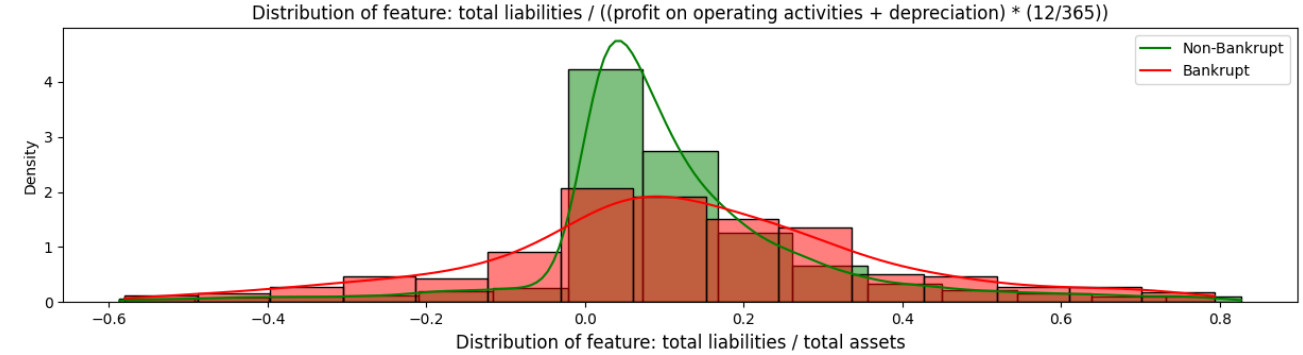
```
# We will make histograms for a few attributes but separate for Bankrupt Compan
ies and Non-bankrupt Companies

import matplotlib.gridspec as gridspec
import random

attributes=[DF.columns[i] for i in random.sample(range(0,64),30)]
nplots=np.size(attributes)
plt.figure(figsize=(15,4*nplots))
gs = gridspec.GridSpec(nplots,1)
for i, att in enumerate(attributes):
    fig = plt.subplot(gs[i])
    data=filter(DF[att])
    data_status_0=data[DF['Status After 4 Years']==0]
    data_status_1=data[DF['Status After 4 Years']==1]
    sns.histplot(data_status_0, stat="density", kde=True, color="green", bins=1
5)
    sns.histplot(data_status_1, stat="density", kde=True, color="red", bins=15)

    fig.legend(['Non-Bankrupt', 'Bankrupt'],loc='best')
    fig.set_xlabel('')
    fig.set_title('Distribution of feature: ' + att)
```

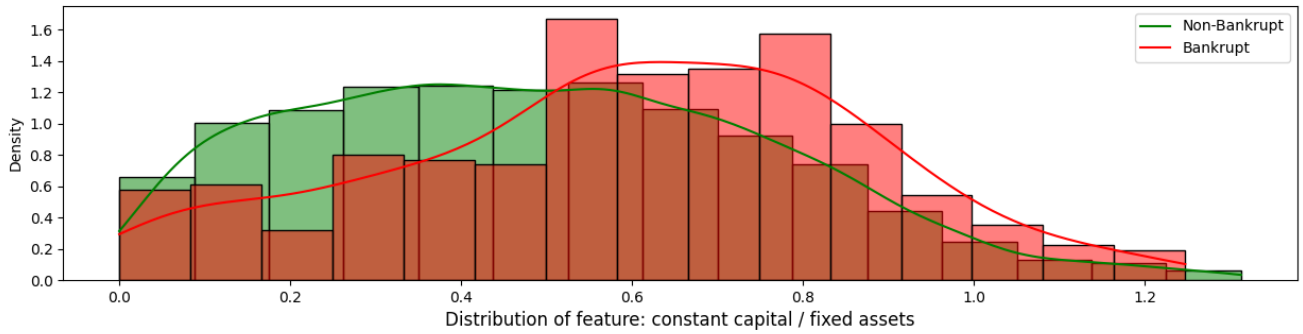

Distribution of feature: (current assets - inventory - short-term liabilities) / (sales - gross profit - depreciation)
Non-Bankrupt
Bankrupt
Density

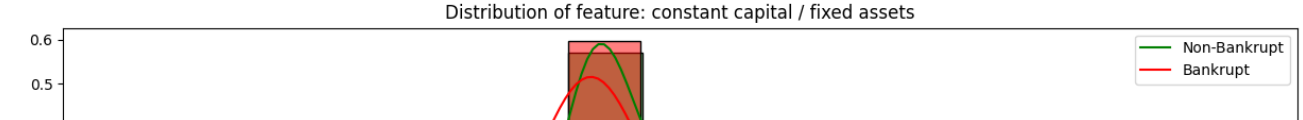

Distribution of feature: gross profit / sales
Non-Bankrupt
Bankrupt
Density

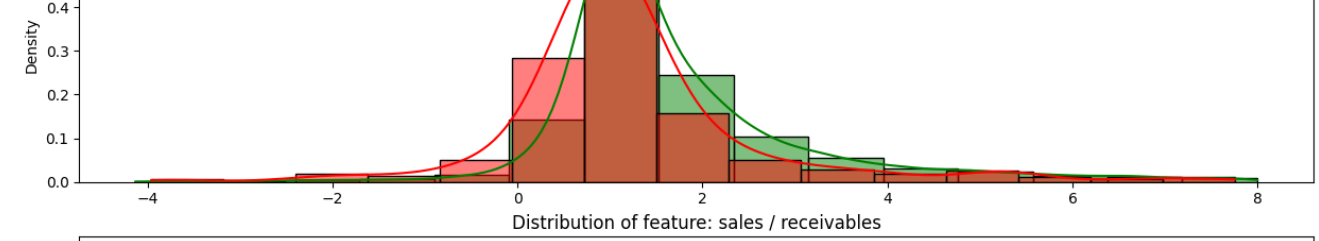

Distribution of feature: gross profit / short-term liabilities
Non-Bankrupt
Bankrupt
Density


Distribution of feature: (gross profit + extraordinary items + financial expenses) / total assets
Non-Bankrupt
Bankrupt
Density

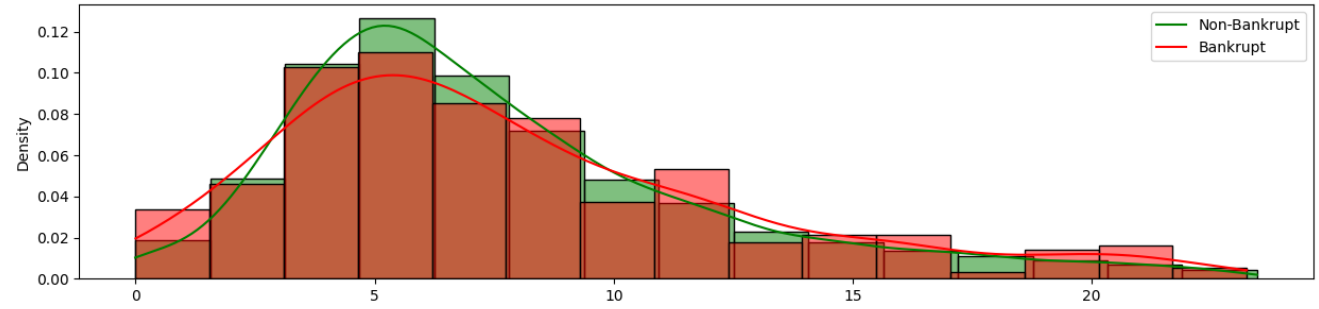

Distribution of feature: total liabilities / ((profit on operating activities + depreciation) * (12/365))
Non-Bankrupt
Bankrupt
Density


Distribution of feature: total liabilities / total assets
Non-Bankrupt
Bankrupt
Density

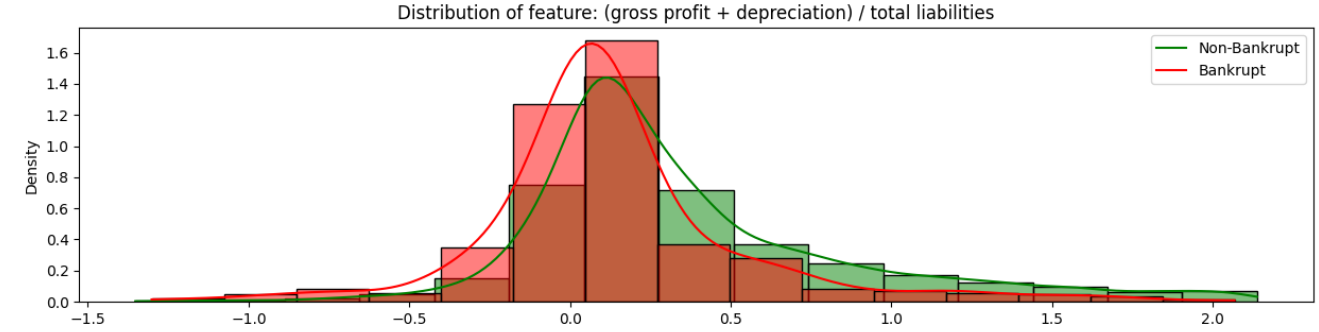

Distribution of feature: constant capital / fixed assets
Non-Bankrupt
Bankrupt



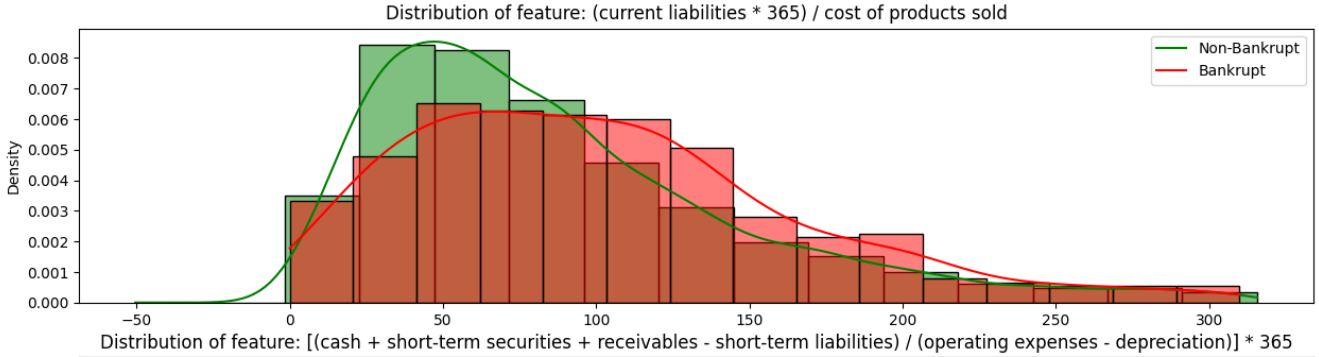
Distribution of feature: sales / receivables



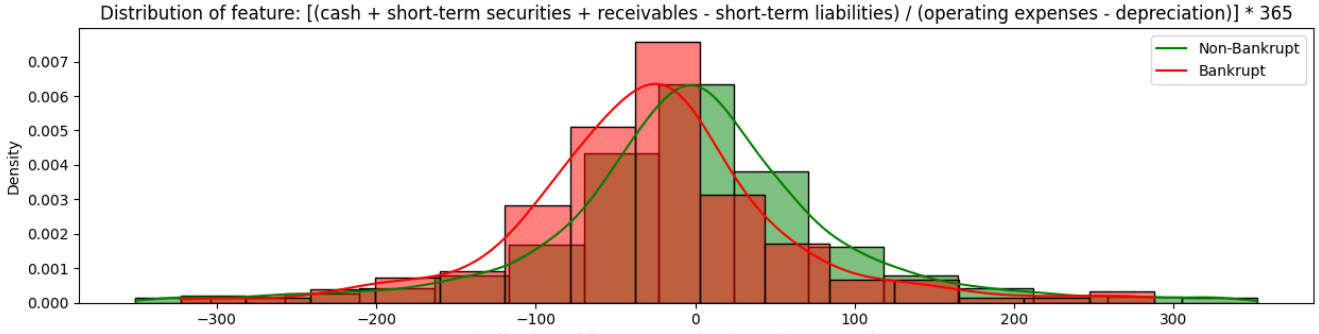
Distribution of feature: (gross profit + depreciation) / total liabilities



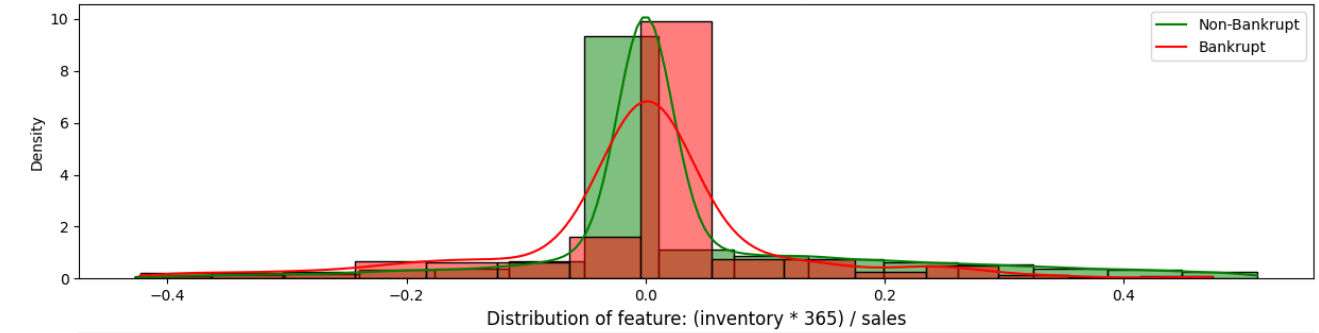
Distribution of feature: (current liabilities * 365) / cost of products sold



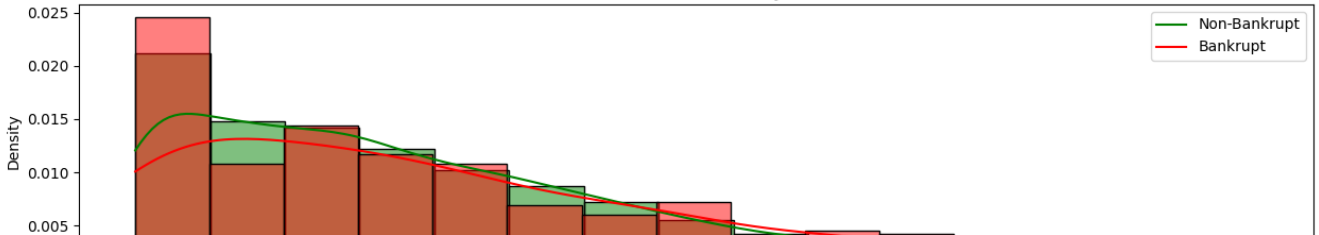
Distribution of feature: [(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365

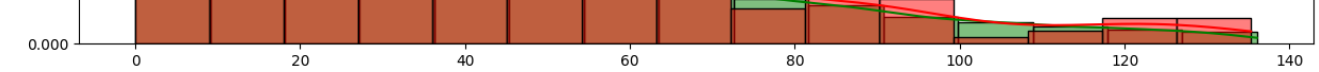


Distribution of feature: retained earnings / total assets

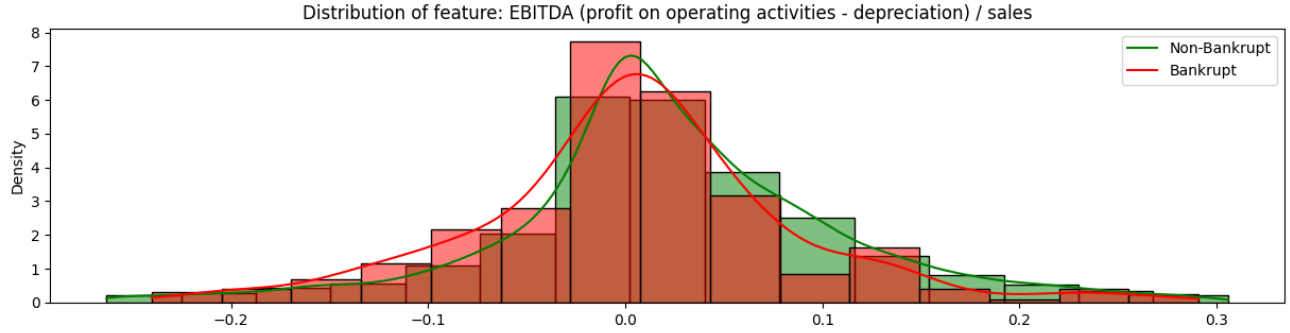


Distribution of feature: (inventory * 365) / sales

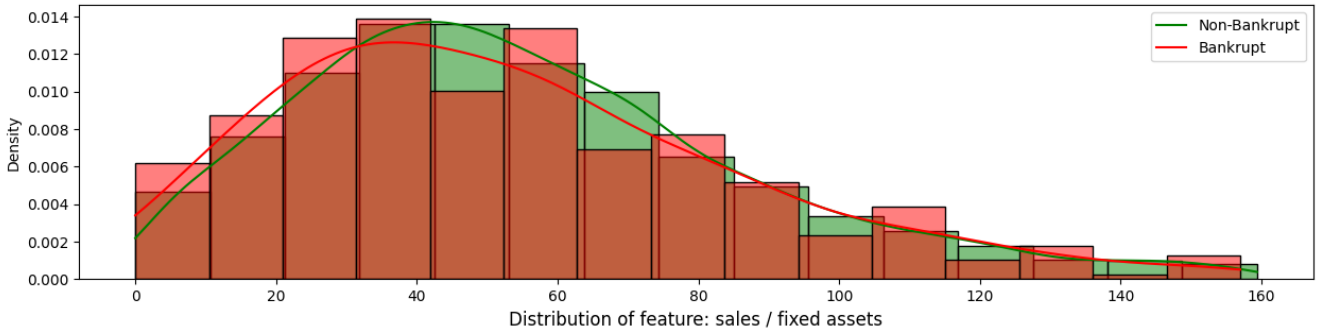




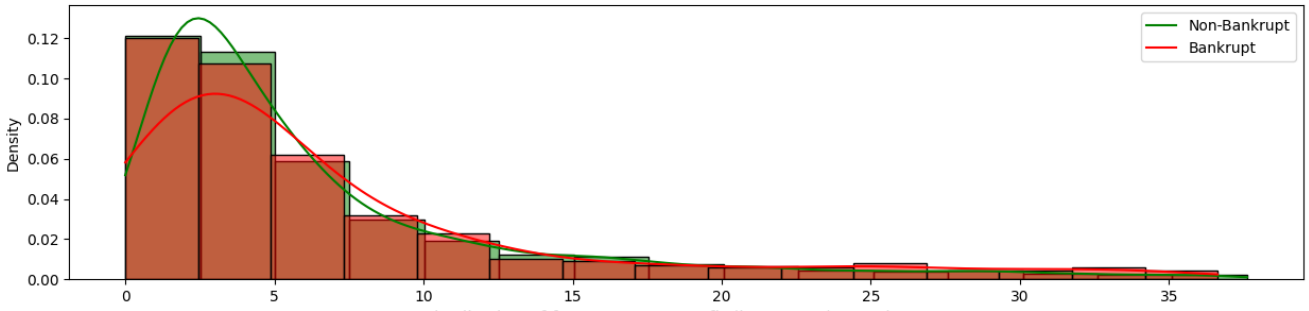
Distribution of feature: EBITDA (profit on operating activities - depreciation) / sales



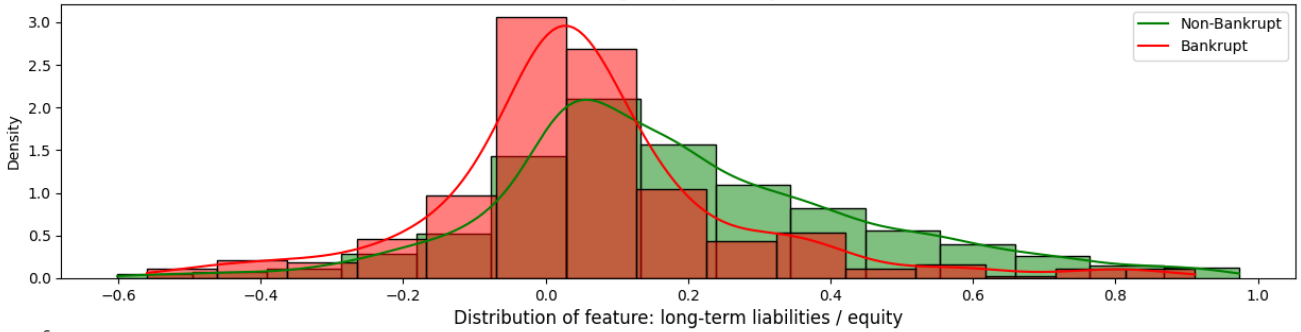
Distribution of feature: (receivables * 365) / sales



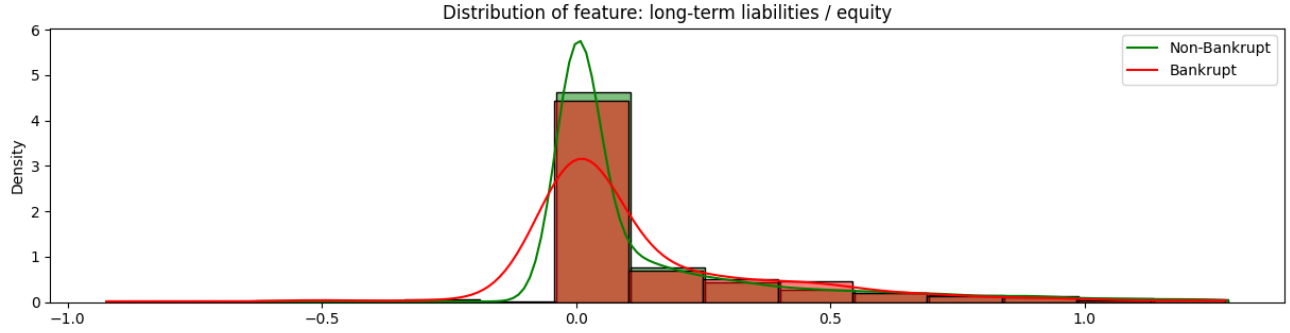
Distribution of feature: sales / fixed assets



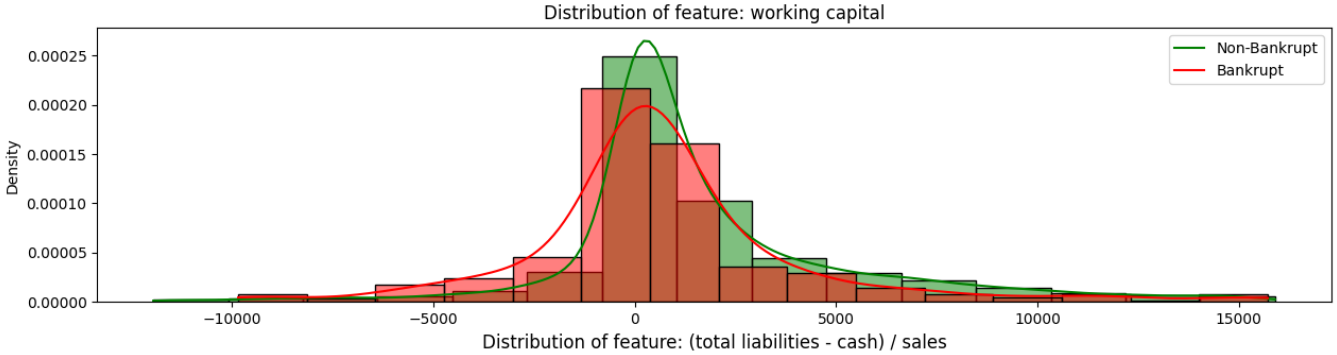
Distribution of feature: gross profit (in 3 years) / total assets



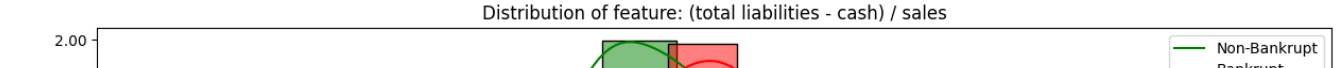
Distribution of feature: long-term liabilities / equity

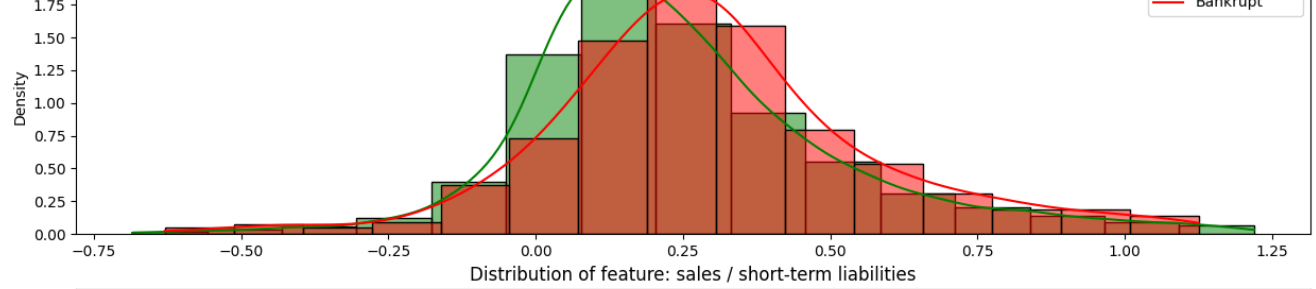


Distribution of feature: working capital

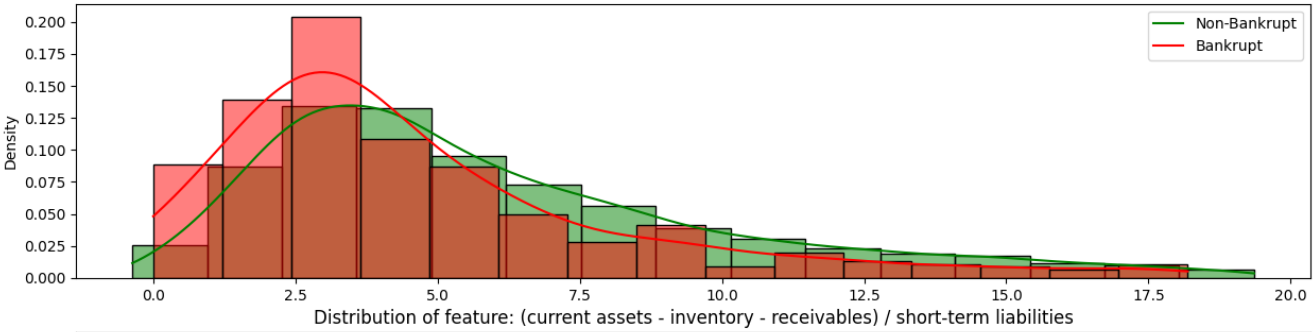


Distribution of feature: (total liabilities - cash) / sales

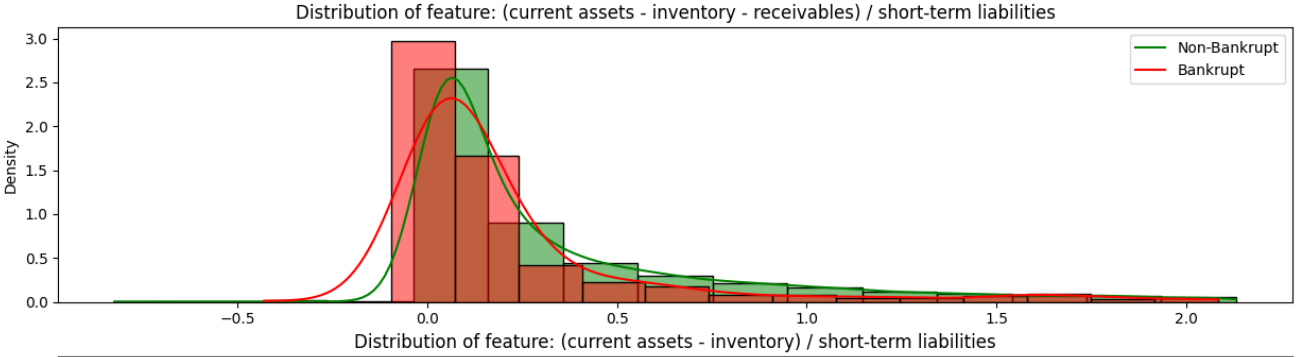




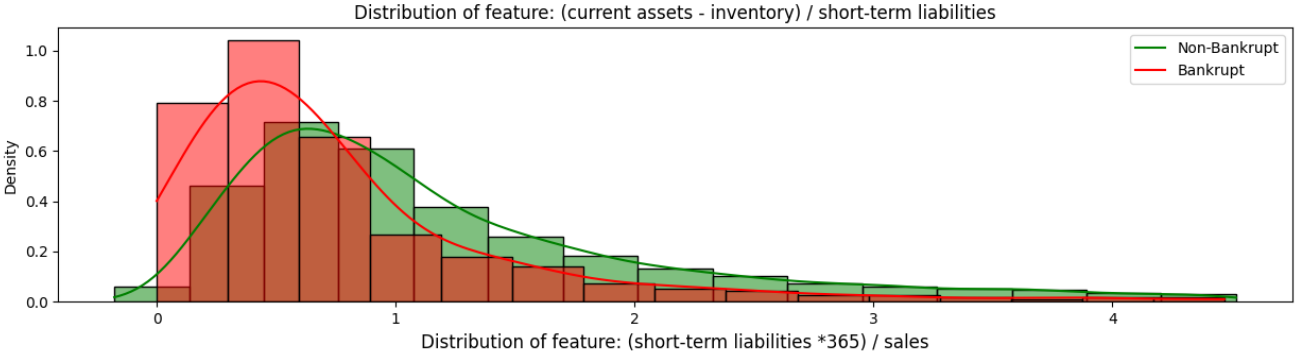
Distribution of feature: sales / short-term liabilities



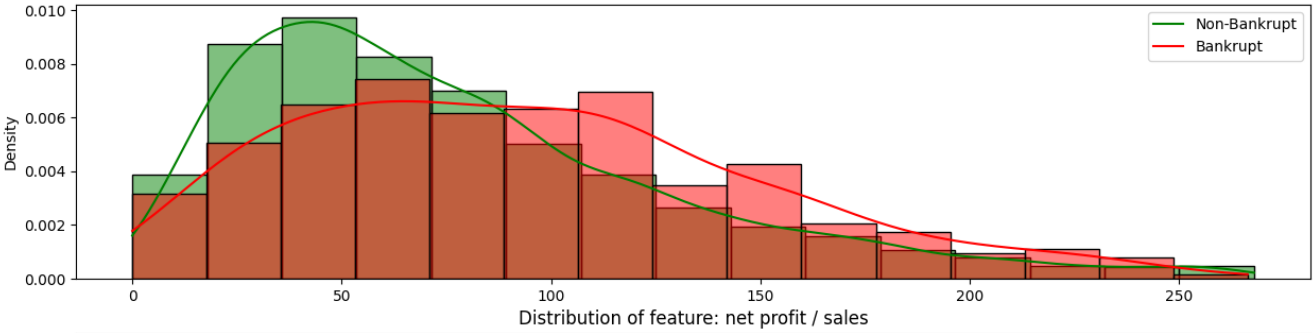
Distribution of feature: (current assets - inventory - receivables) / short-term liabilities



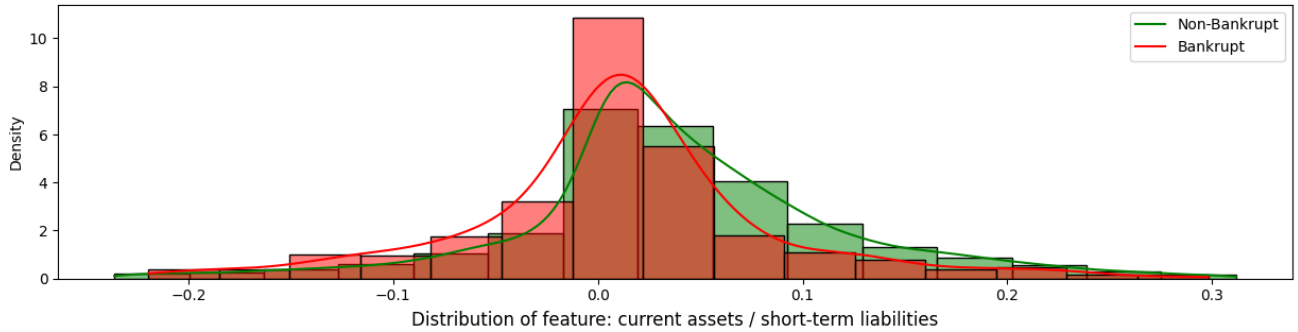
Distribution of feature: (current assets - inventory) / short-term liabilities



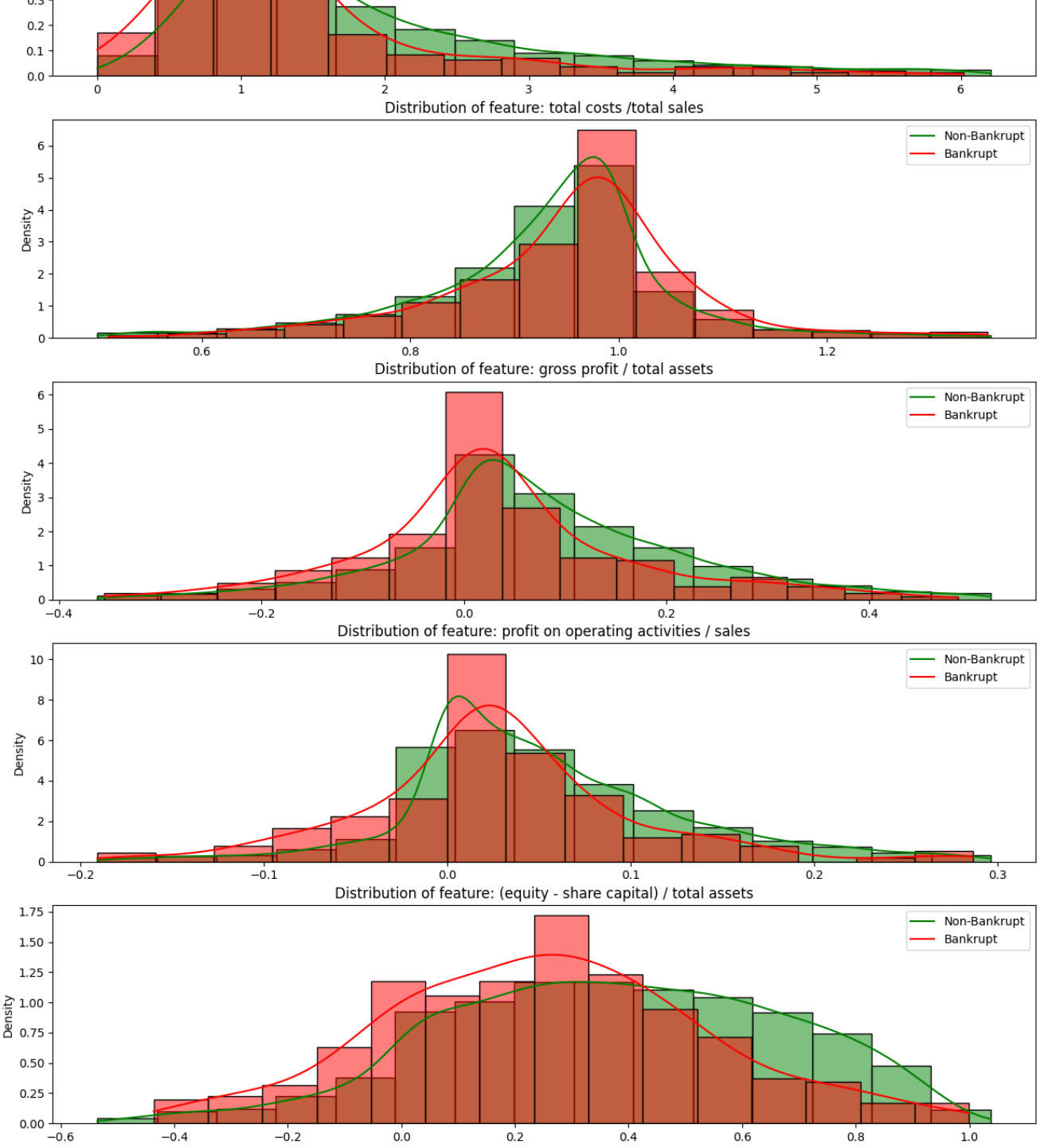
Distribution of feature: (short-term liabilities *365) / sales



Distribution of feature: net profit / sales



Distribution of feature: current assets / short-term liabilities

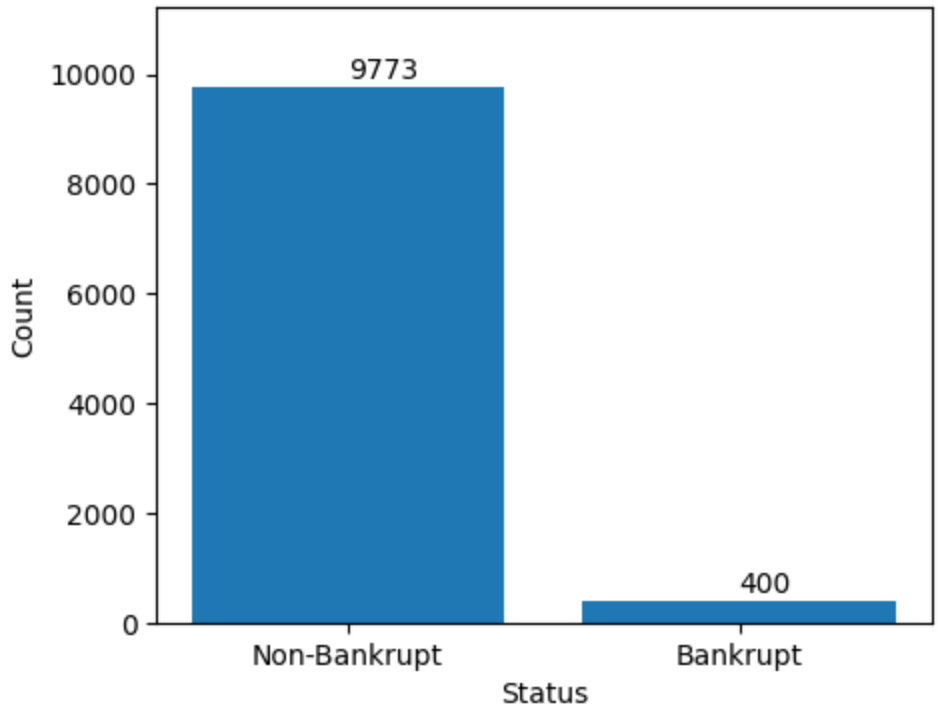


In the above plots, we attempted to visualize how different are the density distributions of the data points for Bankrupt and Non-bankrupt companies, for different features. In other words, we tried to find whether the data points in the two categories belonged to similar populations or clearly different populations.

From the first level analysis, it appears that for majority of the features, the data points from two categories belong to very similar populations or distributions.

This means that it will be very challenging to make accurate predictions about the bankruptcy status.

In [ ]:
```
# Let us also visualize how many instances of bankrupt and non-bankrupt companies we have
a=DF.groupby('Status After 4 Years')['Status After 4 Years'].count()
plt.figure(figsize=(5,4))
plt.bar(height=a,x=['Non-Bankrupt','Bankrupt'])
plt.ylabel('Count')
plt.xlabel('Status');
plt.text(0,a[0]+150,str(a[0]))
plt.text(1,a[1]+150,str(a[1]))
plt.ylim(0,1.15*a[0]);
```

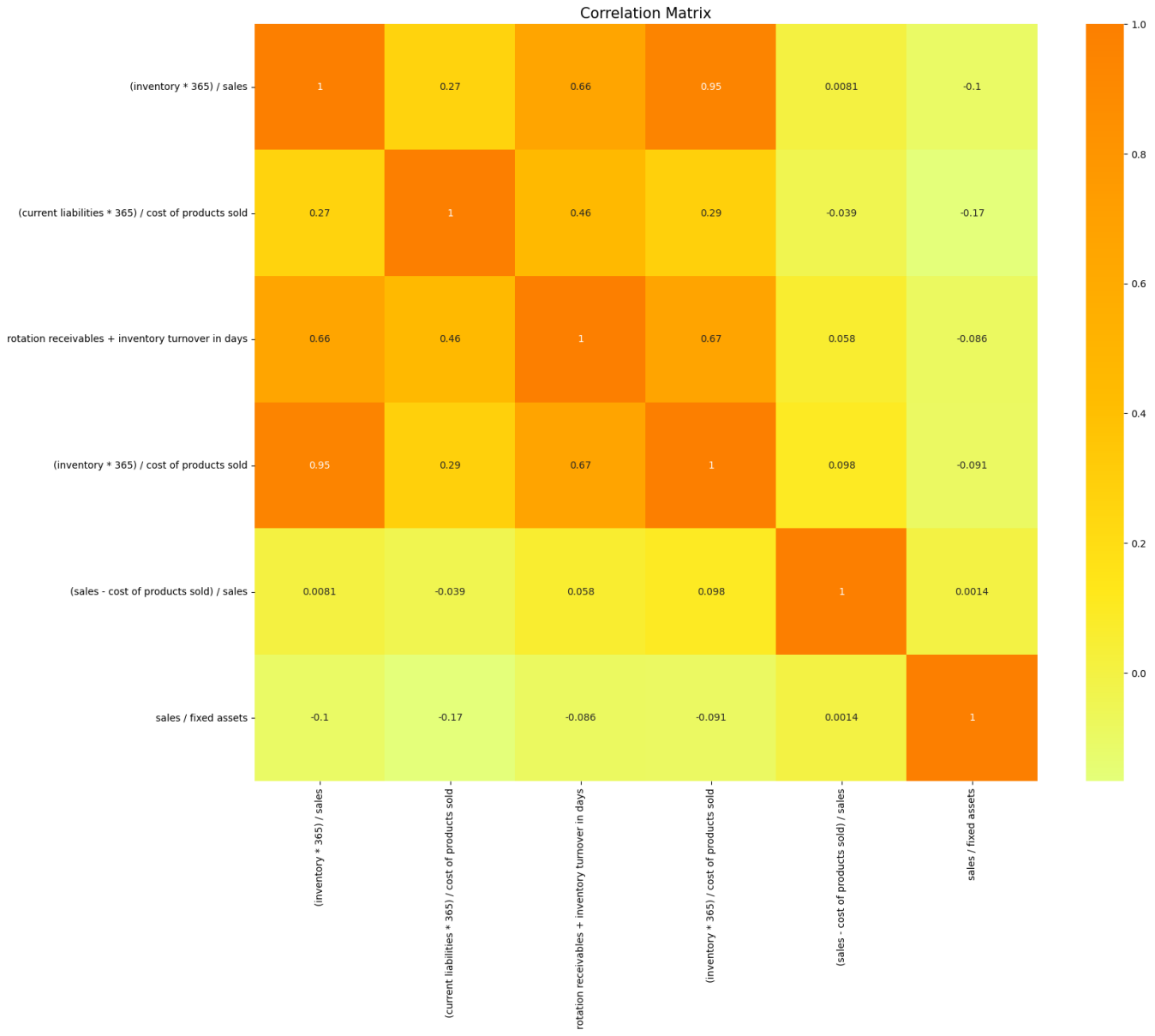


Since, more than 96% of the datapoints available are Non-bankrupt companies, it is safe to say that our dataset is not balanced.
This information is important in the choice of machine learing model.
For example, a model like KNN would be a bad choice in this scenerio.

Next, we will check the relationship between different attributes using correlation matrix

In [ ]:

```
plt.figure(figsize=(18,14))
a1=filter(DF.loc[:,[DF.columns[19]]])
a2=filter(DF.loc[:,[DF.columns[31]]])
a3=filter(DF.loc[:,[DF.columns[42]]])
a4=filter(DF.loc[:,[DF.columns[46]]])
a5=filter(DF.loc[:,[DF.columns[55]]])
a6=filter(DF.loc[:,[DF.columns[63]]])
d=np.c_[a1,a2,a3,a4,a5,a6]

data_plot=pd.DataFrame(data=d,columns=[DF.columns[19],DF.columns[31],DF.columns
[42],DF.columns[46],DF.columns[55],DF.columns[63]])

sns.heatmap(data_plot.corr(),cmap='Wistia',annot=True)
plt.title('Correlation Matrix',fontsize=15);
```



From the above correlation matrix, we can see that some attributes have practically no correlation with each other while some have correlation coefficient as high as 0.95.
This gives us an important clue that in our data cleaning step, we should eliminate some attributes which are highly correlated to others. This can be achieved by techniques such as Principal Component Analysis (PCA).

In [ ]:
```
# Checking number of missing values
# This will help identify if a column has too many missing values
missing=[]
for i in range(0,64):
   n=(DF[DF.columns[i]])
   m=np.isnan(n)
   missing.append(len(n[m]))

ind=[]
for i in range(0,64):
   if missing[i]>1000:
      ind.append(i)
      print("Maximum Number of Missing Data Points in a column are",missing[i])
      print("In column:",DF.columns[i])
      print("At Index:",i)
```

```
Maximum Number of Missing Data Points in a column are 3164
In column: sales (n) / sales (n-1)
At Index: 20
Maximum Number of Missing Data Points in a column are 4518
In column: (current assets - inventories) / long-term liabilities
At Index: 36
```

In [ ]:
```
# Removing columns where number of missing values are more than 1000
# Because these number are relatively significant with respect to total number
 of datapoints

DF_new=DF.copy(deep=True)
col=[DF.columns[i] for i in ind]
DF_new=DF_new.drop(columns=col)
```

In [ ]:
```
# Now, replacing missing vaues with the mean of the entire column

for i in range(0,DF_new.shape[1]-1):

   a=DF_new[DF_new.columns[i]]
   I=np.isnan(a)
   a[I]=np.nanmean(a)
```

Before proceeding further,
We will split our dataset into Training Set (75%) and Test Set (25%) This should be done here to ensure that our decision in futher process are not influenced by test set data

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [ ]:
```
X_Train, X_Test, y_Train, y_Test = train_test_split(DF_new.iloc[:,0:DF_new.shap
e[1]-1],DF_new.iloc[:,DF_new.shape[1]-1], test_size=0.25, random_state=40)
```

We shall standardize the test and training data, as we will implement PCA technique afterwards which works if the data is standardized.

In [ ]:
```
# Standardizing the Training Set as well as the Test Set
scaler=StandardScaler()
scaler.fit(X_Train.values)
D=scaler.transform(X_Train.values)
X_Train_Std= pd.DataFrame(D, index=X_Train.index, columns=X_Train.columns)
D=scaler.transform(X_Test.values)
X_Test_Std= pd.DataFrame(D, index=X_Test.index, columns=X_Test.columns)
```

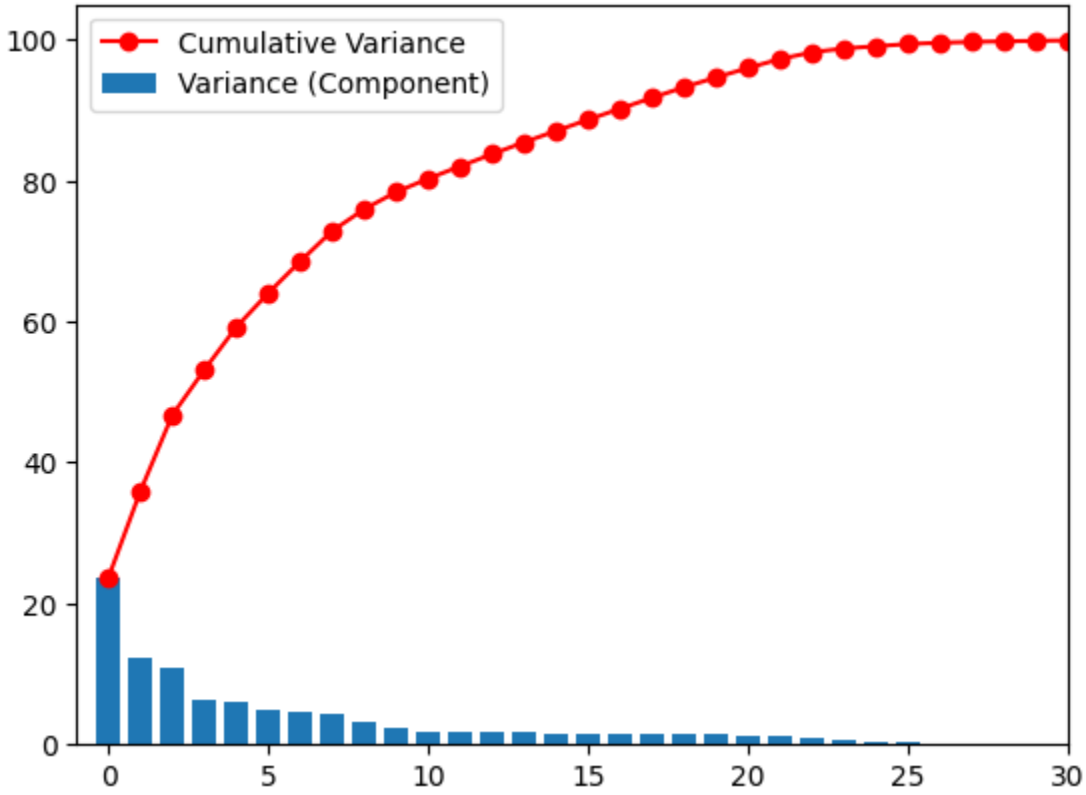
In [ ]:
```
# Computing the data covariance matrix
S=np.cov(X_Train_Std.T)
S.shape
```

Out[ ]:
```
(62, 62)
```

In [ ]:
```
# Computing Eigen Vectors and Eigen Values

eigenValues, eigenVectors = np.linalg.eigh(S)
idx = (eigenValues).argsort()[::-1]
eigenValues = eigenValues[idx]
eigenVectors = eigenVectors[:, idx]
```

In [ ]:

```
# Calculating the number of components required to cover 98% of variance present in data
eigValSum = sum(eigenValues)
expVar = [eigV/eigValSum*100 for eigV in eigenValues]
cumExpVar = np.cumsum(expVar)

plt.bar(range(len(expVar)), expVar, label='Variance (Component)')
plt.plot(cumExpVar, 'r-o', label='Cumulative Variance')
plt.xlim(-1,30)
plt.legend()
plt.show()

variance=0.98
for idx, cumulativeSum in enumerate(np.cumsum(eigenValues) / np.sum(eigenValues)):
   print(idx,cumulativeSum)
   if cumulativeSum > variance:
     break
```




```
0 0.23578071425336578
1 0.3586362764578271
2 0.46696744057968304
3 0.531277543392259
4 0.5919696407854645
5 0.6403303576800368
6 0.6854263887071114
7 0.7286137768416511
8 0.7593529960790243
9 0.7838481085273363
10 0.8027296997184242
11 0.8203498509810087
12 0.8375828634570421
13 0.8544726604889669
14 0.8705684886801048
15 0.8864649903469534
16 0.9020441599556333
17 0.9175188863728803
18 0.9325580510608146
19 0.9464027916006933
20 0.9598231644957473
21 0.9725026730809644
22 0.9821387174407344
```

In [ ]:
```
# Therefore, the basis vectors matrix can be calculated as below,
B=eigenVectors[:,0:idx+1]

# We get updated Data-Frames as below,
col=[('f'+str(i+1)) for i in range(0,idx+1)]
X_Red_Train=np.dot(X_Train_Std,B)
X_Red_Train=pd.DataFrame(data=X_Red_Train,columns=col)
X_Red_Test=np.dot(X_Test_Std,B)
X_Red_Test=pd.DataFrame(data=X_Red_Test,columns=col)
```

In [ ]:
```
# Training Set will look as below with only 23 attributes (instead of 62) which are made by linear combination of the 62 attributes
# It is to be noted here that, while reducing the number of attributes, we have lost only 2% of the information content, rest 98% we have preserved
X_Red_Train
```

Out[ ]:

	f1	f2	f3	f4	f5	f6	f7	f8	f9	
0	-0.247954	0.136422	0.031125	-0.083658	-0.114264	0.018377	-0.039029	0.096307	-0.039052	-1.572
1	0.059499	0.077180	0.032157	-0.109410	-0.218593	0.026044	-0.056597	-0.009502	-0.055738	0.029
2	0.015418	0.225106	0.005461	0.035699	0.173931	0.020734	-0.046704	0.051671	-0.008107	0.039
3	-0.058170	0.259621	-0.000634	0.011527	0.078888	0.018625	-0.062042	0.039051	-0.017138	0.045
4	0.064939	0.036834	0.044602	-0.087445	-0.169052	0.013945	-0.008334	0.030596	0.092912	0.031
...	...	...	...	...	...	...	...	...	...	
7624	0.100245	0.184563	-0.007639	-0.084092	-0.188219	0.033287	-0.110182	-0.071797	-0.077428	0.025
7625	0.026996	0.122593	0.023657	-0.088982	-0.170577	0.022401	-0.053927	0.005074	-0.039419	0.034
7626	0.002320	-0.034819	0.080395	-0.064741	-0.032153	0.010109	0.076272	0.089563	0.006242	0.038
7627	0.077200	0.205919	-0.010018	-0.046256	-0.051886	0.024255	-0.061589	-0.015658	-0.041431	0.028
7628	0.092072	0.040514	0.023833	-0.097451	-0.189886	0.025332	-0.027789	-0.009408	-0.073577	-0.002

7629 rows × 23 columns

In [ ]:
```
# Test Set will look as below,
X_Red_Test
```

Out[ ]:

	f1	f2	f3	f4	f5	f6	f7	f8	f9	
0	0.031513	0.193560	0.000864	-0.053219	-0.104144	0.022488	-0.067893	-0.023096	0.015420	0.034
1	-0.068684	0.264336	-0.017802	1.429963	4.270987	-0.002298	0.206467	0.987864	-0.068601	0.087
2	0.056279	0.044550	0.044764	-0.082426	-0.135257	0.018126	0.014219	0.020061	-0.026905	0.030
3	0.119035	-0.024826	0.066995	-0.125685	-0.268074	0.020420	-0.031063	-0.015935	0.190840	0.021
4	-0.069856	0.212846	0.013642	0.032576	0.106601	0.017376	-0.063014	-0.004401	-0.041415	0.040
...	...	...	...	...	...	...	...	...	...	
2539	0.040116	0.052166	0.044917	-0.090506	-0.158042	0.019968	-0.024196	0.024462	-0.036338	0.031
2540	0.011743	0.092949	0.039488	-0.079191	-0.113672	0.014650	-0.003261	0.033571	-0.015852	0.035
2541	0.079868	0.007916	0.054390	-0.097120	-0.173753	0.018067	-0.011054	0.024251	0.029610	0.029
2542	0.115878	-0.032363	0.060680	-0.123102	-0.258742	0.023369	-0.032655	-0.016688	-0.030050	0.024
2543	0.037223	0.000444	0.030902	0.141012	0.405962	0.013484	0.026880	0.185444	-0.010487	0.017

2544 rows × 23 columns

Now that we have our dataset with reduced dimensionality,
we will calculate Area Under Curve Metrics (AUC) for all features with respect to status of bankruptcy. This will give us important information about which feature is more capable of predicting the status and which feature has just the same distribution for both Bankrupt and Non-bankrupt

In [ ]:
```
from sklearn.mixture import GaussianMixture
from sklearn.metrics import roc_auc_score
```

In [ ]:
```
feature_names=X_Red_Train.columns[0:23]
auc_Train=[]

for feature in feature_names:
    X_Train_=X_Red_Train[feature]
    gm = GaussianMixture(n_components=1,random_state=0)
    gm.fit((X_Train_.values).reshape(-1,1))
    p_Train = gm.score_samples((X_Train_.values).reshape(-1,1))

    auc_Train.append(roc_auc_score(y_Train,-1*p_Train))

Columns =['feature','AUC for Training Set']
S=np.c_[feature_names,auc_Train]
df_scores=pd.DataFrame(data=S,columns=Columns)
df_scores
```

Out[ ]:

	feature	AUC for Training Set
0	f1	0.587163
1	f2	0.406335
2	f3	0.649398
3	f4	0.595875
4	f5	0.568845
5	f6	0.522229
6	f7	0.483861
7	f8	0.48026
8	f9	0.476279
9	f10	0.3993
10	f11	0.486568
11	f12	0.537423
12	f13	0.480765
13	f14	0.546786
14	f15	0.434606
15	f16	0.510514
16	f17	0.533666
17	f18	0.554027
18	f19	0.565715
19	f20	0.487708
20	f21	0.534806
21	f22	0.52896
22	f23	0.517095

From above table, we see that AUC score for almost all features are close to 0.5, i.e. the above table tells that, financial data in year 2 of study is not an ideal candidate for predicting bankupty status after 4 years.

However, we will still try two different machine learning models and evaluate their performance.

Machine Learning Model - 1 : Gaussian Mixture Model

First, we will try to fit a Gaussian Mixture Model with different number of Gaussians and components on training set. We will select this model as this model is good at detecting outliers/anomalies or data points out of the concerned distribution:

In [ ]:
```
X_Train=X_Red_Train.copy(deep=True)
X_Test=X_Red_Test.copy(deep=True)
X_Train['Status After 4 Years']=y_Train

# We will fit the model for non-bankrupt with only one class : Non-Bankrupt
X_Train_0=X_Train[(X_Train['Status After 4 Years'])==0]
X_Train_0=X_Train_0.drop(columns='Status After 4 Years')

# We will fit the model for Bankrupt (when we use Two Gaussians) with only one
 class : Bankrupt
X_Train_1=X_Train[(X_Train['Status After 4 Years'])==1]
X_Train_1=X_Train_1.drop(columns='Status After 4 Years')

X_Train=X_Train.drop(columns='Status After 4 Years')
```

In [ ]:
```
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import accuracy_score
```

In [ ]:
```
# Defining a function which will return optimum threshold value based on F1 sco
re

def opt_threshold(target,p_values):

   tr_sort = sorted(p_values)
   List_Find_Threshold=[1, 10, 20, 30, 50 , 90, 160, 250, 380, 500, 650 , 850,
1100, 1400, 1800, 2300];
   F1_score=np.zeros(len(List_Find_Threshold))
   threshold=np.zeros(len(List_Find_Threshold))

   for i in range(0,len(List_Find_Threshold)):
        tr = tr_sort[ List_Find_Threshold[i]]
        threshold[i]=tr
        F1_score[i]=f1_score(target, p_values < tr)

   ind=np.argmax(F1_score)
   return(threshold[ind],F1_score[ind])
```

In [ ]:
```
# Trial-1
# One Gaussian, One Component
gm1 = GaussianMixture(n_components=1,random_state=0)
gm1.fit(X_Train_0)

p_Train = gm1.score_samples(X_Train)

Threshold,F1=opt_threshold(y_Train,p_Train)

precision_Train=precision_score(y_Train, p_Train < Threshold)
recall_Train=recall_score(y_Train, p_Train < Threshold)
F1_Train=f1_score(y_Train, p_Train < Threshold)
accuracy_Train=accuracy_score(y_Train, p_Train < Threshold)

print("F1 score for Model 1 for Training Set is ",F1_Train)
print("Precision for Model 1 for Training Set is ",precision_Train)
print("Recall for Model 1 for Training Set is ",recall_Train)
print("Accuracy for Model 1 for Training Set is ",accuracy_Train)
```

```
F1 score for Model 1 for Training Set is  0.08079376328844791
Precision for Model 1 for Training Set is  0.05181818181818182
Recall for Model 1 for Training Set is  0.1832797427652733
Accuracy for Model 1 for Training Set is  0.8299908244855158
```

In [ ]:
```
# Trial-2
# One Gaussian, Three Components
gm1 = GaussianMixture(n_components=3,random_state=0)
gm1.fit(X_Train_0)

p_Train = gm1.score_samples(X_Train)

Threshold,F1=opt_threshold(y_Train,p_Train)

precision_Train=precision_score(y_Train, p_Train < Threshold)
recall_Train=recall_score(y_Train, p_Train < Threshold)
F1_Train=f1_score(y_Train, p_Train < Threshold)
accuracy_Train=accuracy_score(y_Train, p_Train < Threshold)

print("F1 score for Model 2 for Training Set is ",F1_Train)
print("Precision for Model 2 for Training Set is ",precision_Train)
print("Recall for Model 2 for Training Set is ",recall_Train)
print("Accuracy for Model 2 for Training Set is ",accuracy_Train)
```

```
F1 score for Model 2 for Training Set is  0.08221119773210489
Precision for Model 2 for Training Set is  0.05272727272727273
Recall for Model 2 for Training Set is  0.1864951768488746
Accuracy for Model 2 for Training Set is  0.8302529820422073
```

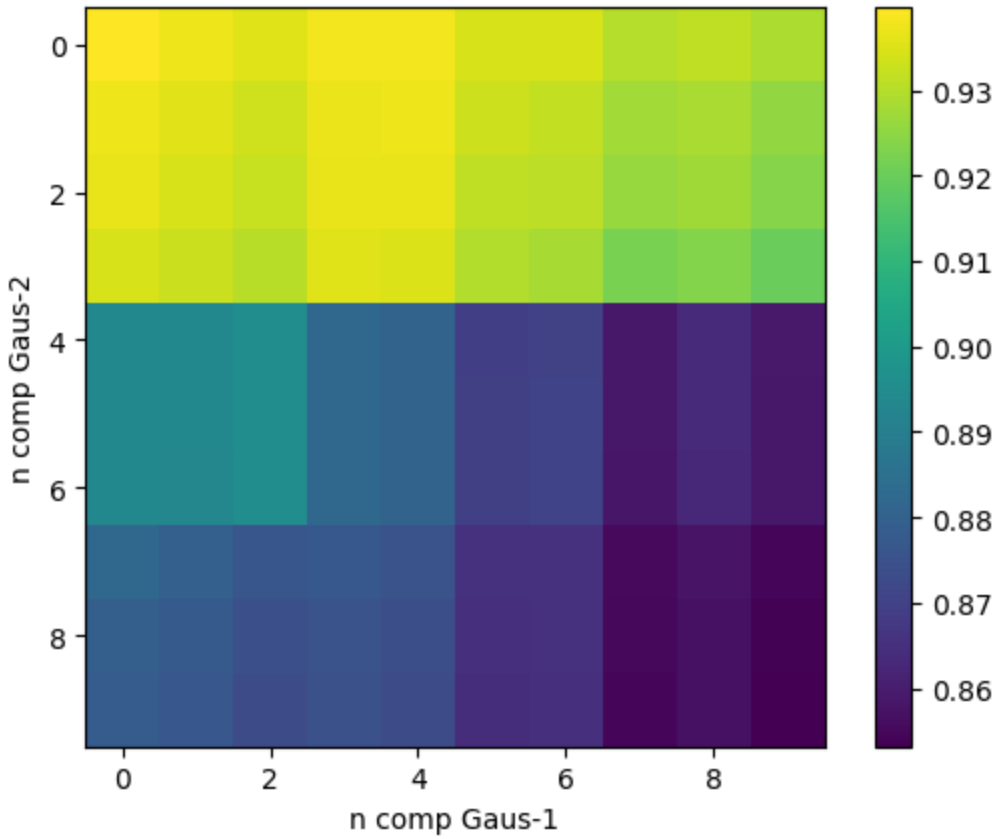
In [ ]:

```
# Trial-3
# Two Gaussians
# Gaussian-1 for non-bankrupt : 3 components
# Gaussian-2 for bankrupt : 2 components
gm1 = GaussianMixture(n_components=3,random_state=0)
gm1.fit(X_Train_0)
p1 = gm1.score_samples(X_Train)

gm2 = GaussianMixture(n_components=2,random_state=0)
gm2.fit(X_Train_1)
p2 = gm2.score_samples(X_Train)

c=np.arange(0.1,10.1,0.1)
F1_score=np.zeros(len(c))
for i in range(0,len(c)):
  F1_score[i]=f1_score(y_Train, p1 >(c[i])*p2)

ind=np.argmax(F1_score)
c=c[ind]


precision_Train=precision_score(y_Train, p1>c*p2)
recall_Train=recall_score(y_Train, p1>c*p2)
F1_Train=f1_score(y_Train, p1>c*p2)
accuracy_Train=accuracy_score(y_Train, p1>c*p2)

print("F1 score for Model 3 for Training Set is ",F1_Train)
print("Precision for Model 3 for Training Set is ",precision_Train)
print("Recall for Model 3 for Training Set is ",recall_Train)
print("Accuracy for Model 3 for Training Set is ",accuracy_Train)
```

```
F1 score for Model 3 for Training Set is  0.11584699453551911
Precision for Model 3 for Training Set is  0.08774834437086093
Recall for Model 3 for Training Set is  0.17041800643086816
Accuracy for Model 3 for Training Set is  0.8939572683182593
```

In [ ]:

```
# Trial-4
# Two Gaussians with fewer features

# Tuning Hyper-parameters

Train_Accuracy=np.full((10,10),0.0)

feat=['f1','f3','f4','f5','f14','f18','f19']

for i in range(0,10):

    for j in range(0,10):

       gm1 = GaussianMixture(n_components=i+1,random_state=0)
       gm1.fit(X_Train_0[feat])
       p1 = gm1.score_samples(X_Train[feat])

       gm2 = GaussianMixture(n_components=j+1,random_state=0)
       gm2.fit(X_Train_1[feat])
       p2 = gm2.score_samples(X_Train[feat])

       c=np.arange(0.1,10.1,0.1)
       acc=np.zeros(len(c))
       for k in range(0,len(c)):
           acc[k]=accuracy_score(y_Train, p1 >(c[k])*p2)

       ind=np.argmax(acc)
       c=c[ind]
       accuracy_Train=accuracy_score(y_Train, p1>c*p2)
       Train_Accuracy[i,j]=accuracy_Train

T=plt.imshow(Train_Accuracy,interpolation='none')
plt.colorbar(T);
plt.xlabel('n comp Gaus-1')
plt.ylabel('n comp Gaus-2');
```



In [ ]:
```
gm1 = GaussianMixture(n_components=1,random_state=0)
gm1.fit(X_Train_0[feat])
p1 = gm1.score_samples(X_Train[feat])

gm2 = GaussianMixture(n_components=2,random_state=0)
gm2.fit(X_Train_1[feat])
p2 = gm2.score_samples(X_Train[feat])

c=np.arange(0.1,10.1,0.1)
acc=np.zeros(len(c))
for k in range(0,len(c)):
    acc[k]=accuracy_score(y_Train, p1 >(c[k])*p2)

ind=np.argmax(acc)
c=c[ind]

precision_Train=precision_score(y_Train, p1>c*p2)
recall_Train=recall_score(y_Train, p1>c*p2)
F1_Train=f1_score(y_Train, p1>c*p2)
accuracy_Train=accuracy_score(y_Train, p1>c*p2)

print("F1 score for Model 4 for Training Set is ",F1_Train)
print("Precision for Model 4 for Training Set is ",precision_Train)
print("Recall for Model 4 for Training Set is ",recall_Train)
print("Accuracy for Model 4 for Training Set is ",accuracy_Train)
```

```
F1 score for Model 4 for Training Set is  0.03636363636363636
Precision for Model 4 for Training Set is  0.04891304347826087
Recall for Model 4 for Training Set is  0.028938906752411574
Accuracy for Model 4 for Training Set is  0.9374754227290601
```

In [ ]:
```
# Now lets measure accuracy for the Model 4 on Test Set

p1= gm1.score_samples(X_Test[feat])
p2= gm2.score_samples(X_Test[feat])

precision_Train=precision_score(y_Test, p1>c*p2)
recall_Train=recall_score(y_Test, p1>c*p2)
F1_Train=f1_score(y_Test, p1>c*p2)
accuracy_Train=accuracy_score(y_Test, p1>c*p2)

print("F1 score for Model 4 for Test Set is ",F1_Train)
print("Precision for Model 4 for Test Set is ",precision_Train)
print("Recall for Model 4 for Test Set is ",recall_Train)
print("Accuracy for Model 4 for Test Set is ",accuracy_Train)
```

```
F1 score for Model 4 for Test Set is  0.06535947712418301
Precision for Model 4 for Test Set is  0.078125
Recall for Model 4 for Test Set is  0.056179775280898875
Accuracy for Model 4 for Test Set is  0.9437893081761006
```

From above trials, we can say that for this dataset,
Gaussian Mixture Models could not give satisfactory F1 score despite getting good accuracy.

Machine Learning Model - 2: Random Forest Classifier

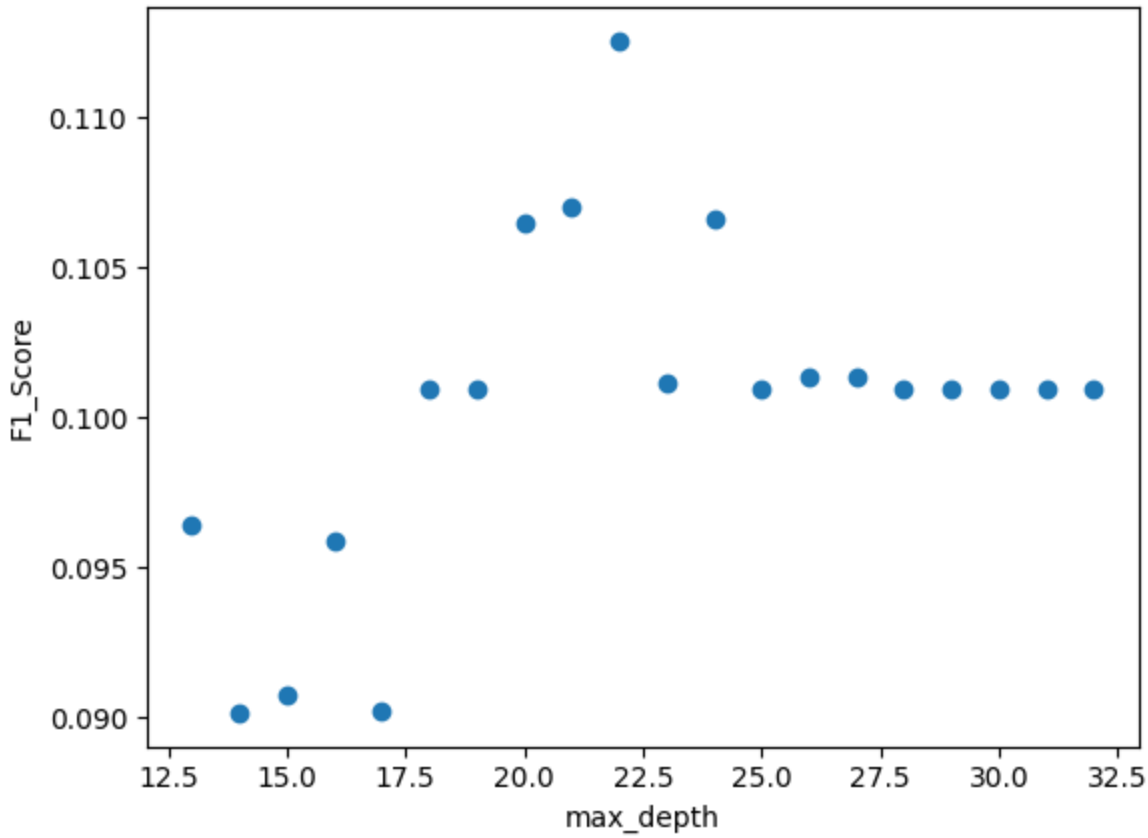
From the work done till now, it is quite evident that our data is not linearly separable. In this case, algorithms such as KNN, SVM, etc would not be a good choice. Therefore, we will try Random Forest Classifier

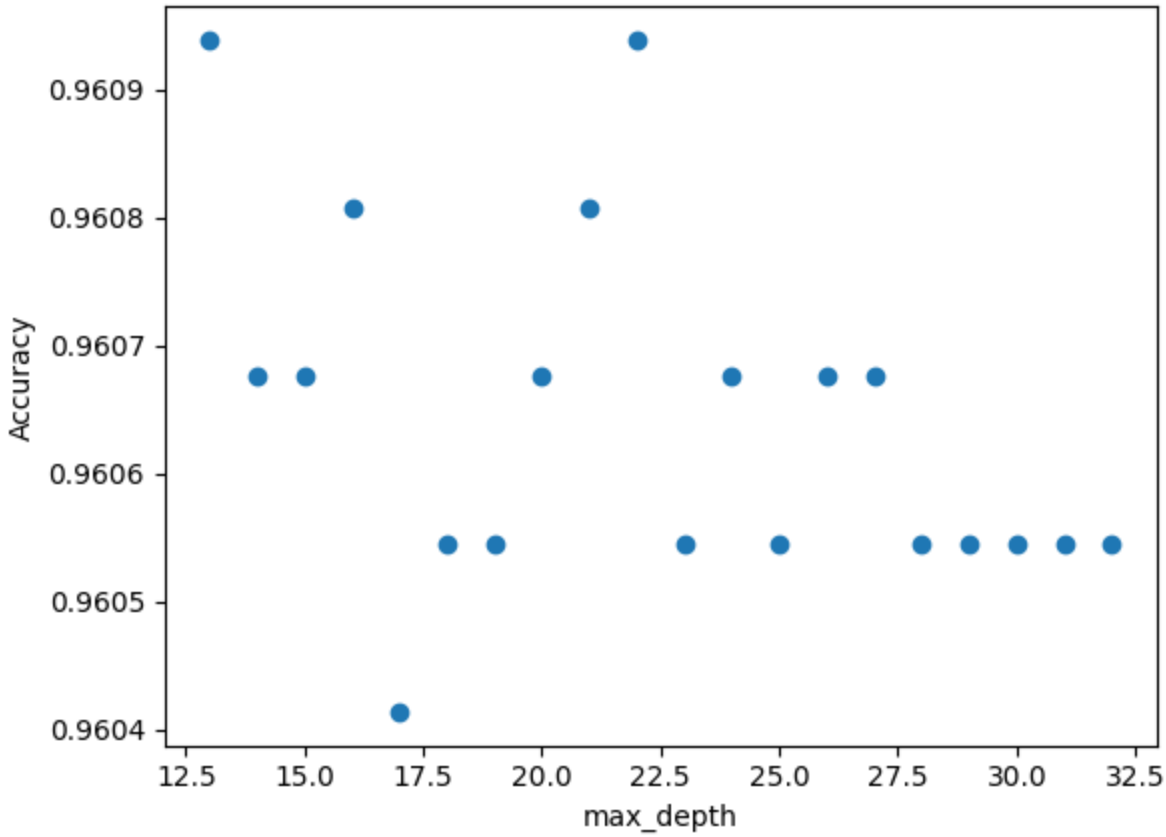
In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer
```

In [ ]:
```
f1_ = np.zeros(20)
acc_=np.zeros(20)
scoring = {'accuracy' : make_scorer(accuracy_score),
           'f1_score' : make_scorer(f1_score)}

# Tuning Hyper-parameters with respect to F1 score
for d in range(12,32):
    randomfor_class= RandomForestClassifier (n_estimators=100,max_depth=d+1,min
_samples_split=5,random_state=10)
    results = cross_validate(estimator=randomfor_class,X=X_Train, y=y_Train,cv=
5, scoring=scoring)

    f1_[d-12]=(results['test_f1_score']).mean()
    acc_[d-12]=(results['test_accuracy']).mean()
```

In [ ]:

```
x=np.arange(13,33,1)
plt.scatter(x,f1_)
plt.xlabel('max_depth')
plt.ylabel('F1_Score')
plt.show()

plt.scatter(x,acc_)
plt.xlabel('max_depth')
plt.ylabel('Accuracy')
plt.show()
```


F1_Score
0.110
0.105
0.100
0.095
0.090
12.5
15.0
17.5
20.0
22.5
25.0
27.5
30.0
32.5
max_depth


Accuracy
0.9609
0.9608
0.9607
0.9606
0.9605
0.9604
12.5
15.0
17.5
20.0
22.5
25.0
27.5
30.0
32.5
max_depth

In [ ]:
```
# Fitting Model as per tuned hyper-parameters
randomfor_class= RandomForestClassifier (n_estimators=100,max_depth=22,min_samp
les_split=5,random_state=10)
randomfor_class.fit(X_Train,y_Train)
y_pred_train=randomfor_class.predict(X_Train)


precision_Train=precision_score(y_Train, y_pred_train)
recall_Train=recall_score(y_Train, y_pred_train)
F1_Train=f1_score(y_Train, y_pred_train)
accuracy_Train=accuracy_score(y_Train, y_pred_train)

print("F1 score for Model 1 for Training Set is ",F1_Train)
print("Precision for Model 1 for Training Set is ",precision_Train)
print("Recall for Model 1 for Training Set is ",recall_Train)
print("Accuracy for Model 1 for Training Set is ",accuracy_Train)
```

```
F1 score for Model 1 for Training Set is  0.8502772643253235
Precision for Model 1 for Training Set is  1.0
Recall for Model 1 for Training Set is  0.7395498392282959
Accuracy for Model 1 for Training Set is  0.9893826189539914
```

In [ ]:
```
# Testing model on Test Set
y_pred_test=randomfor_class.predict(X_Test)


precision_Test=precision_score(y_Test, y_pred_test)
recall_Test=recall_score(y_Test, y_pred_test)
F1_Test=f1_score(y_Test, y_pred_test)
accuracy_Test=accuracy_score(y_Test, y_pred_test)

print("F1 score for Model 1 for Test Set is ",F1_Test)
print("Precision for Model 1 for Test Set is ",precision_Test)
print("Recall for Model 1 for Test Set is ",recall_Test)
print("Accuracy for Model 1 for Test Set is ",accuracy_Test)
```

```
F1 score for Model 1 for Test Set is  0.08163265306122448
Precision for Model 1 for Test Set is  0.4444444444444444
Recall for Model 1 for Test Set is  0.0449438202247191
Accuracy for Model 1 for Test Set is  0.964622641509434
```

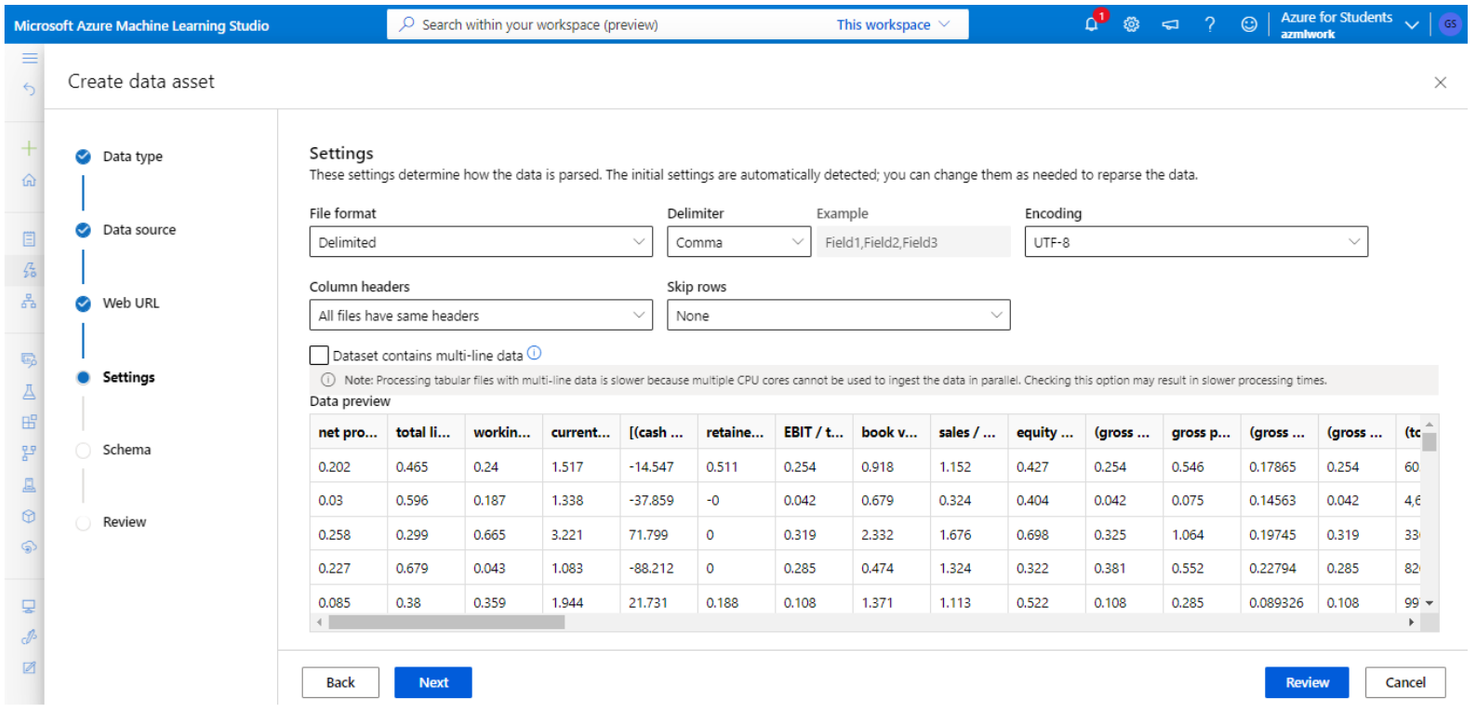
Again, from Random Forest Algorithm, we observe that although we are able to get good accuracy on the test set, but we are getting a poor F1 score.
This is because the two categories: Bankrupt and Non-bankrupt are belonging to very similar distributions with respect to attributes.

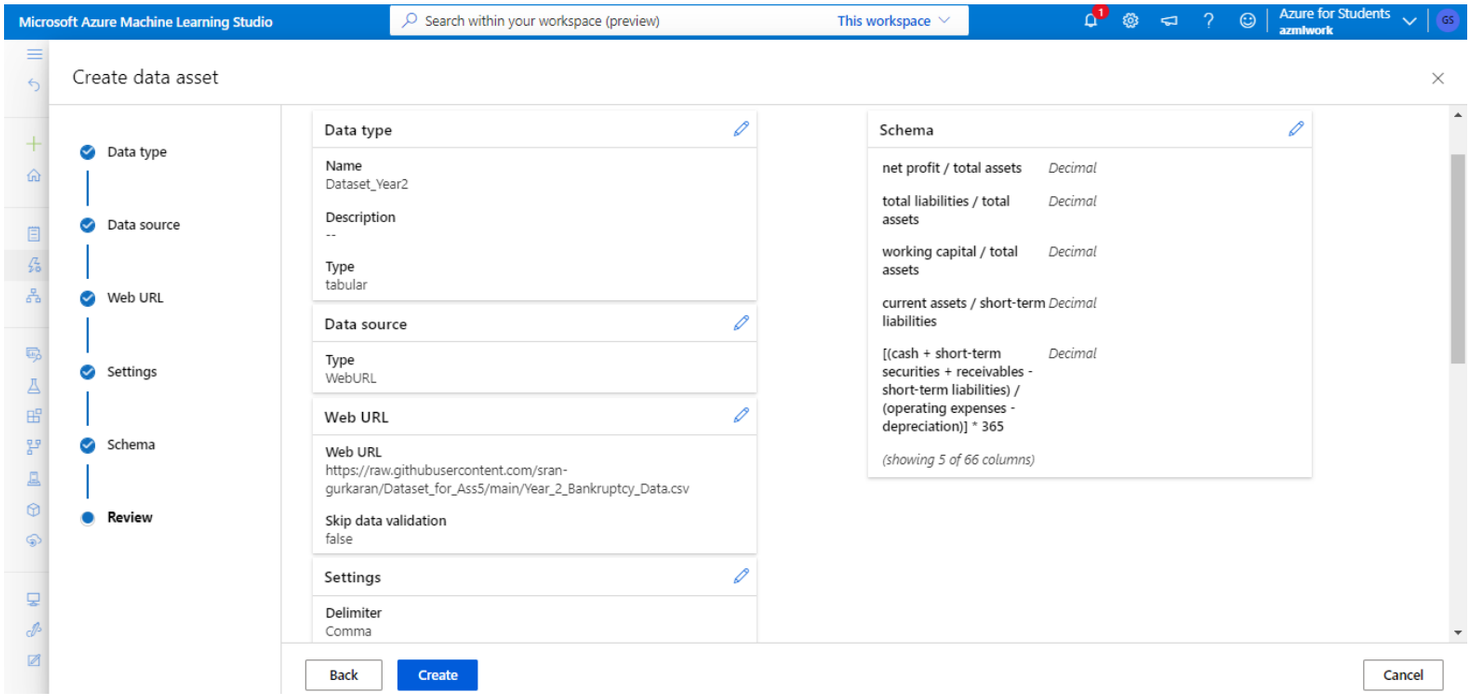
Summary / Conclusion: The two machine learning models that we tried were not able to give satisfactory F1 scores on Test Set

Now that we have tried two different Machine Learning Models manually,
we will now proceed for Automated Machine Learning in Azure Machine Learning and will check if any other classification model is able to give us good F1 score.

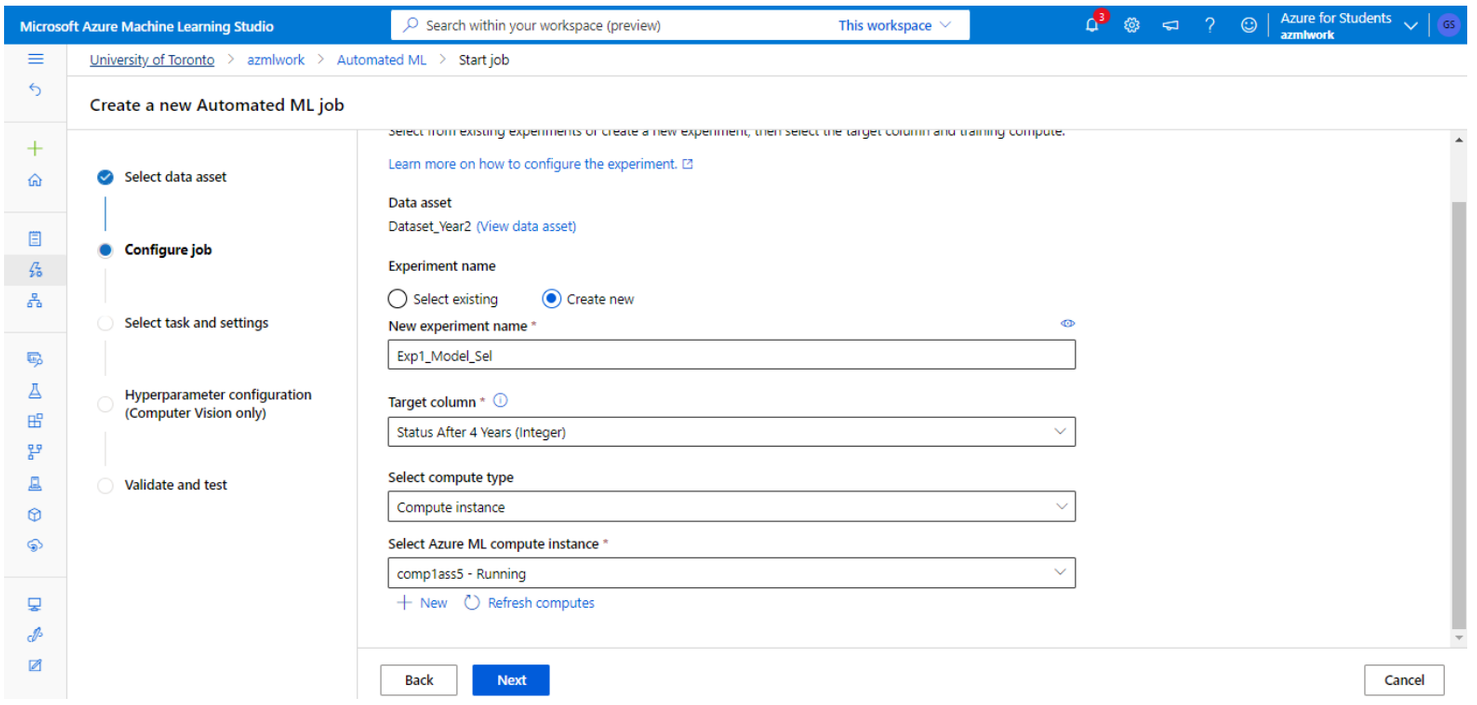
Automated Machine Learning

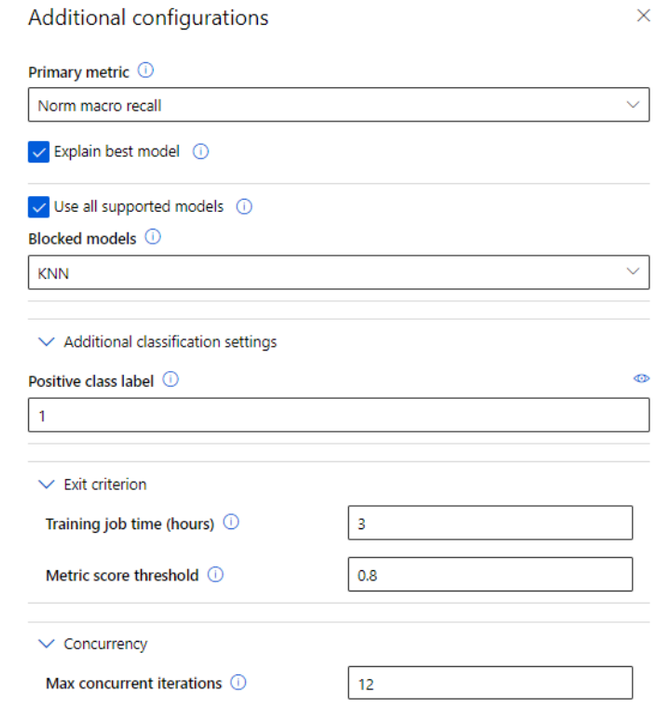
Step 1) Creating Data Asset



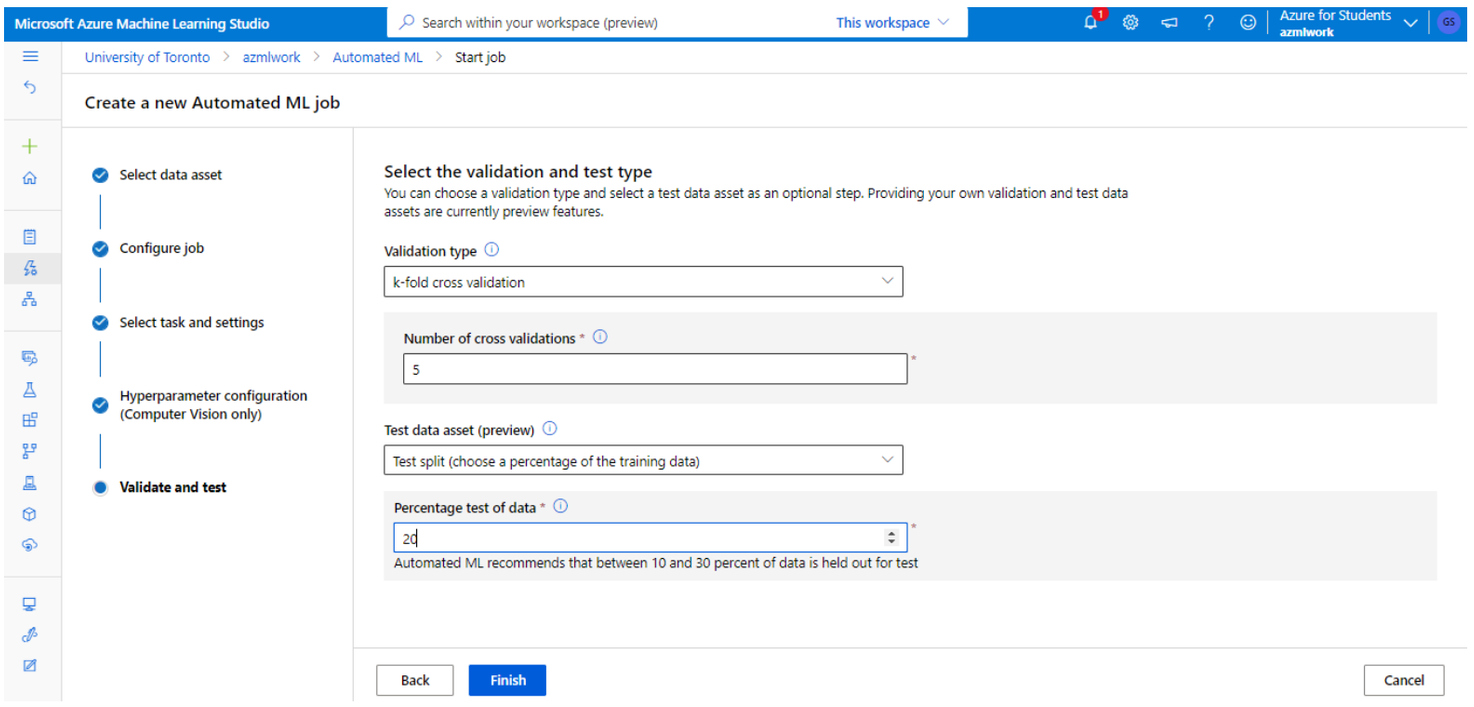


Step 2) Configuring Job

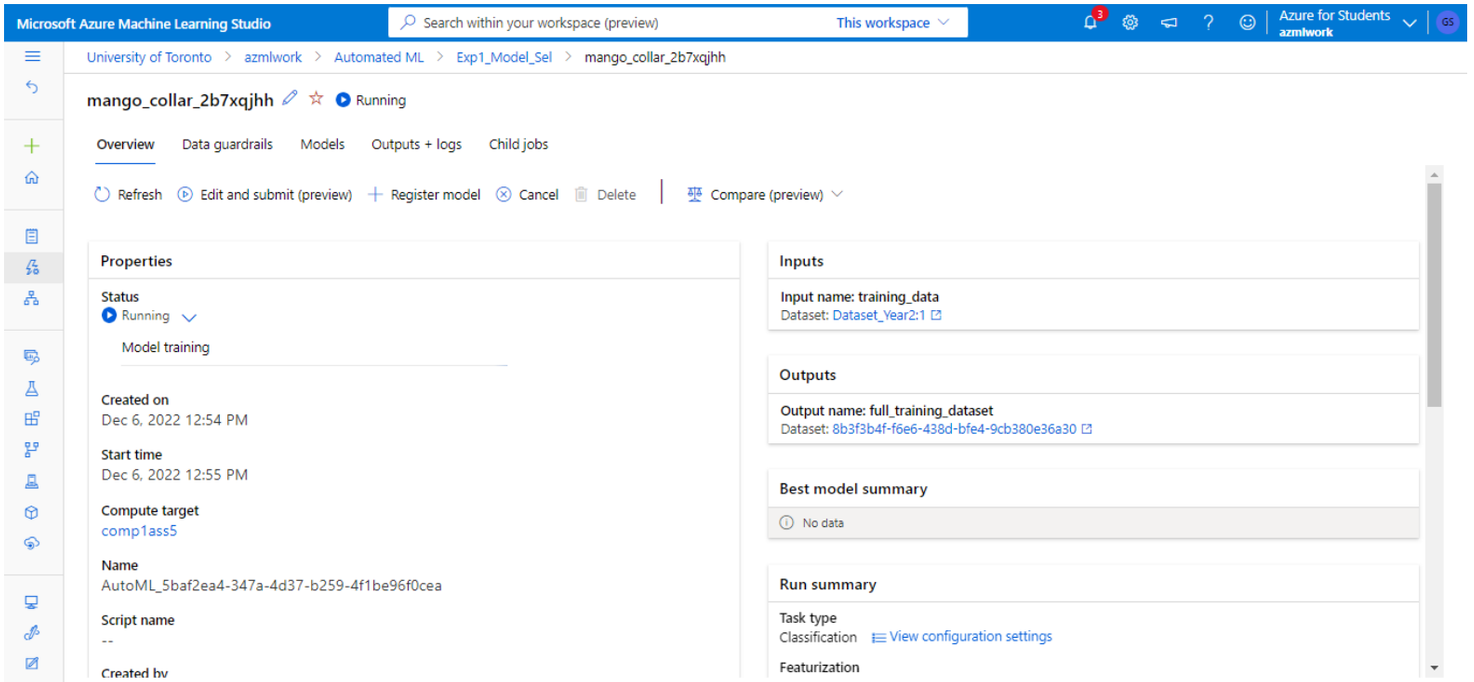




Step 3) Task Settings and Selecting Validation Type



Step 4) Model Training



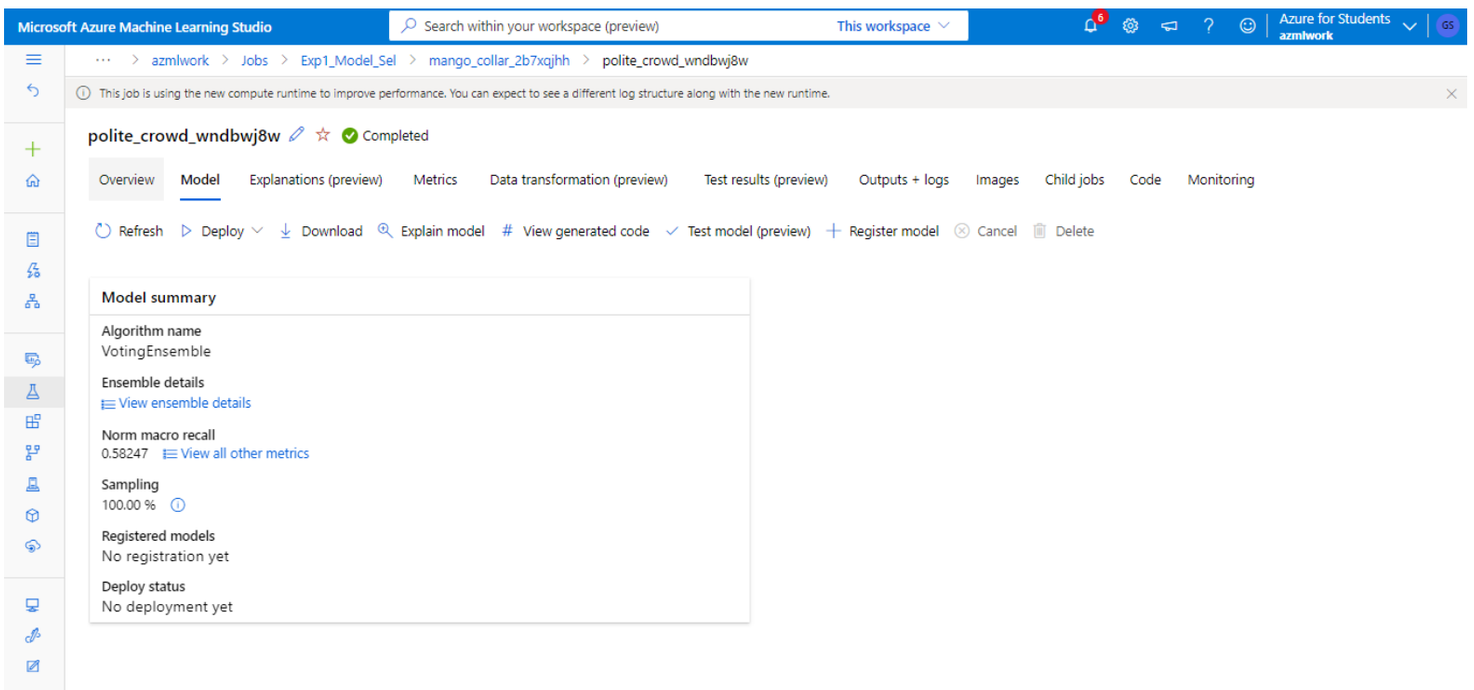
Step 5) Analysing Best Model

Note: Considering the use case of model, we had selected **Norm Macro Recall** as the primary metric.
This is because preventing False Negatives in this case should be avoided as much as possible.

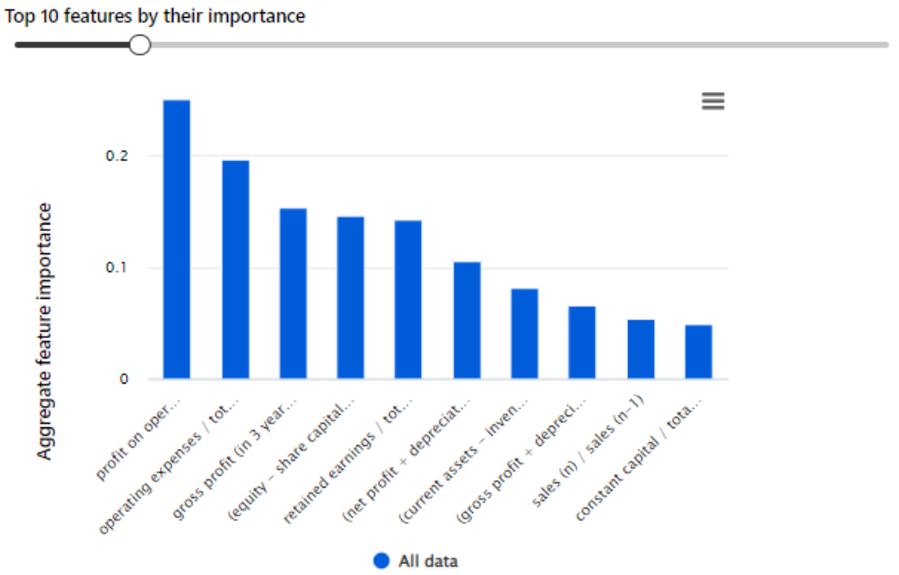
In other words, predicting the status to be non-bankrupt for a company which actually went bankrupt is to be avoided as much as possible.

Best Model : VotingEnsemble

(i) Norm Macro Recall for Best Model : 0.58247

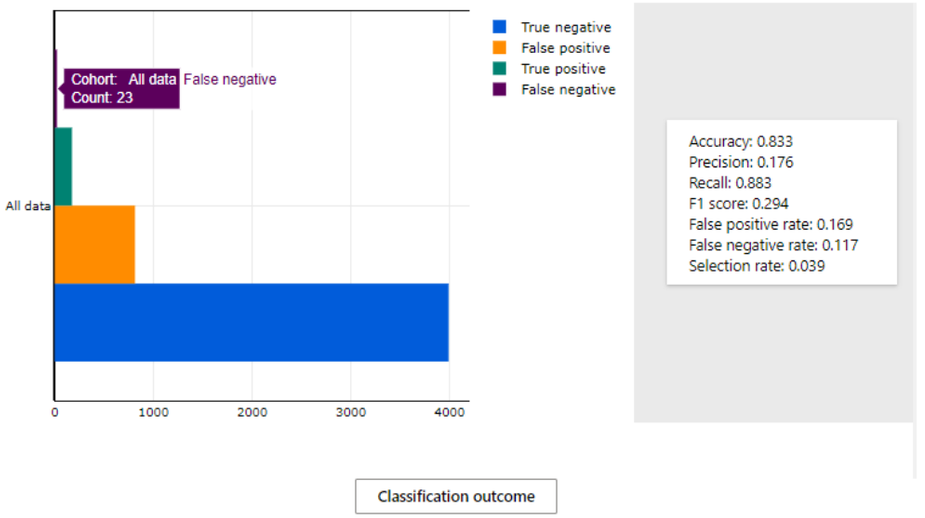


(ii) Feature Importance Analysis by Azure Automated ML :



The above plot shows the top 10 features in the dataset which influence the Target Column : 'Status After 4 Years', as calculated by Automated ML

(iii) Overall Performance and Count of Classification Outcomes out of 5000 data points:



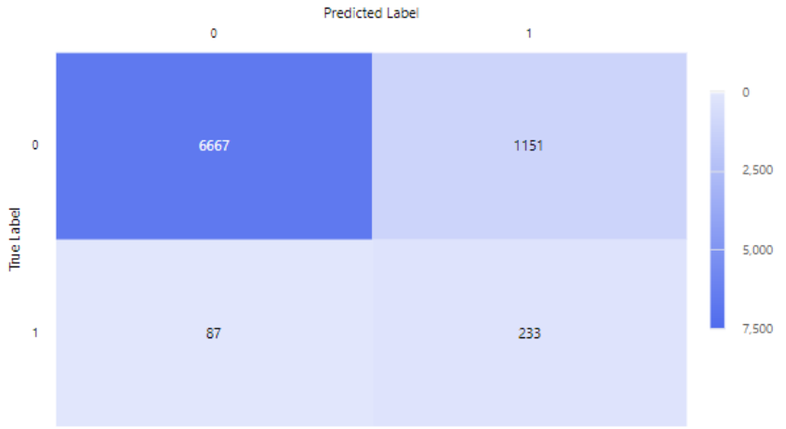
As discussed earlier, our primary objective was to minimize False Negatives, and from model results we can see that model predicted 23 False Negatives out of 5000 data points, which is an acceptable job, however, this comes at a cost of False Positives.

Thus, there is always a trade-off which has to be made depending on the use case.

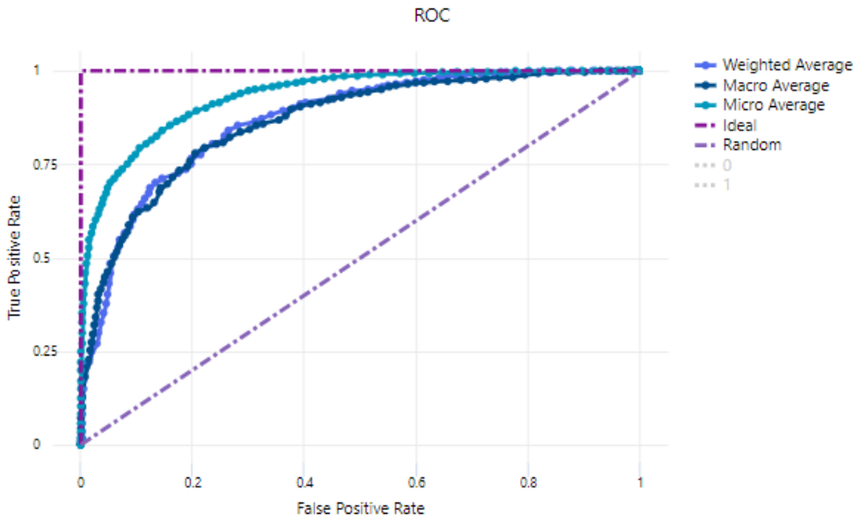
Comparison of Automated Model with Manually Trained Model in Notebook:

In the two models that we trained in the notebook, we could see that accuracy was above 94%, however, recall performance was poor. Here, in the Automated Model where we set Recall Metric to be the primary metric, we observed that we could achieve a model with better recall performance but at the cost of Accuracy which is now only 83%.

(iv) Confusion Matrix on Training Set:
(We had split the data into 80:20 ratio in Train and Test Set)



(v) ROC Curve for Training Data:

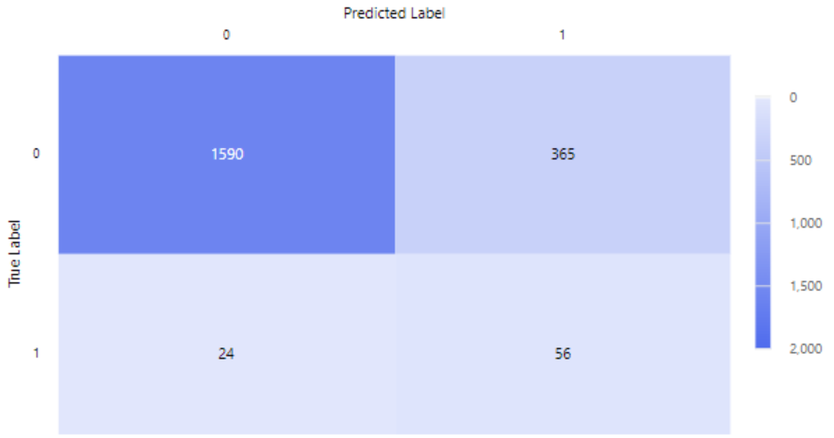


It is to be noted that ROC curve is not about final selected model as this curve is generated using different thresholds on selected algorithm. But, still this curve gives us important information about the algorithm itself.
AUC for this curve, for Macro Average, is 0.87 which is a very descent score. This tells us that the algorithm used for best model is a well suited algorithm for this task and is far better from the random classification for which AUC is 0.5

(vi) Model Performance on Test Set

accuracy	norm_macro_recall
0.8088452	0.5132992

Confusion Matrix on Test Set:



Conclusion : Model performance on Test set is lower than on test set, however, it is still safe to say that model has generalized well enough to perform well for the use case.